VSB – TECHNICAL UNIVERSITY OF OSTRAVA

FACULTY OF ECONOMICS

DIPLOMA THESIS

2019 Xiaoxiao Feng

VSB – TECHNICAL UNIVERSITY OF OSTRAVA FACULTY OF ECONOMICS

DEPARTMENT OF FINANCE

Credit Risk Measuring in Corporates Finance

Měření kreditního rizika ve firemních financích

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Ostrava 2019

VŠB - Technical University of Ostrava
Faculty of Economics
Department of Finance

Diploma Thesis Assignment

Student:	**Bc. Xiaoxiao Feng**
Study Programme:	N6202 Economic Policy and Administration
Study Branch:	6202T010 Finance
Title:	Credit Risk Measuring in Corporate Finance Měření kreditního rizika ve firemních financích
The thesis language:	English

Description:

1. Introduction
2. Characteristics of Credit Risk
3. Description of Theoretical Background and Selected Models
4. Application on Selected Databases
5. Conclusion

Bibliography
List of Abbreviations
Declaration of Utilisation of Results from the Diploma Thesis
List of Annexes
Annexes

References:

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Extent and terms of a thesis are specified in directions for its elaboration that are opened to the public on the web sites of the faculty.

Supervisor: **prof. Ing. Tomáš Tichý, Ph.D.**

Date of issue: 23.11.2018
Date of submission: 26.04.2019

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The declaration

"I hereby declare that I have elaborated the entire thesis including annexes myself."

Ostrava date 26.04.2019

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Content

1. Introduction

By the end of 2017, the number of SMEs in China reached 27.263 million, and the contribution of SMEs to the national fiscal revenue accounted for more than 50%. SMEs' contribution to GDP, fixed assets investment and external direct investment accounted for more than 60%. Technological innovation and new products from SMEs accounted for more than 70%. SMEs provides position for more than 80% urban employees. Contribution of SMEs to new employment accounted for more than 90%. SMEs plays an important role in Chinese economy.

On the other hand, the management system and financial system of SMEs are not as complete as large corporates. It means the financial status of SMEs is not open and transparent. In the same time, there is no efficient credit measuring system or complete credit information database for SMEs as well. Banks take high risk premium because of asymmetric information. As a result, SMEs are hard to finance by credit.

To solve this problem, a database with credit and financial information of the SMEs and a credit measuring system should be established. It takes years to establish a complete database. But it is easier to find efficient credit measuring system for SMEs.

Aim of this thesis is to compute a suitable credit measuring function for SMEs in China. We concentrated on one industry to eliminate impact from different industries. Manufacturing industry was chosen because it is main part of SMEs that it takes more than 90% of SMEs in China.

The second chapter is introduction of credit risk and credit rating. Credit rating industry and SMEs in China is also mentioned.

The third chapter is theoretical part. In order to compute credit measuring function of companies, financial ratios are used, and definition of these ratios are introduced. For further analysis, some analysis methods are applied. Theory and models of these methods are explained in this chapter.

The forth part is practice. Financial information is analyzed. Different credit measuring functions are compute with different analysis methods. At the end of this chapter, the functions are gathered together and compared.

The last chapter is a conclusion of this thesis.

2. Characteristics of Credit Risk

Credit risk is the risk of loss resulting from a borrower's failure to repay a loan or meet contractual obligations. Traditionally, it refers to the risk that lender may not receive the owed principal and interest, which results in an interruption of cash flows and increased costs for lenders to collect. Although it is impossible to know exactly who will default on obligations, properly assessing and managing credit risk can lessen the severity of loss. Interest payments from the borrower or issuer of obligation are a lender's or investor's reward for assuming credit risk.

On another word, credit risk is the possibility that a bank borrower or counterparty will fail to meet its obligations according to agreements. Financial institutions have faced many difficulties over the years and main reason of serious banking problem is lax credit standards for borrowers and counterparties, poor risk management.

The goal of risk management is to control bank's risk within a certain scale and maximize its return. Management of credit risk is a critical part of risk management. Credit risk of bank's portfolio and its individual clients should be managed. The relationship between credit risk and other risk should also be considered.

The largest and most obvious source of credit risk is loan for most banks. It is necessary for bank to collect information and judge risk level of corporate credit in order to prevent credit risk from making loss. The credit risk assessment work conducted by banks including analysis of financial factors, non-financial factors, basic information, behavior analysis and credit guarantee risk analysis.

In practice, commercial banks conduct corporate credit risk analysis including analysis of loan demand, analyzing the purpose of loan, analysis of applicant quality, analyzing if the plan is sensible and analysis of loan limit and so on. In order to reduce potential loss as much as possible and guaranteed loans are paid on time. The analysis of the credit status of credit-granting enterprises has become a key link for commercial banks to carry out credit work.

In developed countries, SMEs collect funds through equity financing. In China, SMEs obtain funds through bank loans. In other words, it is necessary for banks in China to find suitable method to measure credit risk of SMEs.

2.1 Credit Rating

Debt is a promise and credit rating tell lender the probability that borrower will fulfill its promise instead of default. Credit rating is an assessment of borrower's willingness and ability to pay back its debt. The results are expressed in letter grades. Each credit rating letter represents a certain performance strength or a certain credit reliability. For example, Standard & Poor's has a credit rating scale ranging from AAA (excellent) to C and D as it is indicated in table 2.1. A debt instrument with a rating below BB is speculative grade or a junk bond, which means it is more likely to default on loans.

Table 2.1: Credit Rating Level Divided by Big Three

	MOODY'S Long term	MOODY'S Short term	S&P Long term	S&P Short term	FITCH Long term	FITCH Short term	
INVESTMENT GRADE	Aaa		AAA		AAA		HIGHEST
	Aa1		AA+		AA+		
	Aa2		AA		AA	F1+	
	Aa3	Prime 1	AA-	A-1+	AA-		
	A1		A+		A+		
	A2		A	A-1	A	F1	
	A3		A-		A-		
	Baa1	Prime 2	BBB+	A-2	BBB+	F2	
	Baa2		BBB		BBB		
	Baa3	Prime 3	BBB-	A-3	BBB-	F3	
NON-INVESTMENT GRADE	Ba1		BB+		BB+		
	Ba2		BB	B	BB		
	Ba3		BB-		BB-		
	B1		B+		B+	B	
	B2	Not prime	B		B		
	B3		B-		B-		
	Caa		CCC	C	CCC		
	Ca		CC		CC	C	
	C		C		C		
			D	D	D	D	LOWEST

Source: The Association of Corporate Treasurers

Credit rating can be used in any entities that is seeking to borrow money. In addition, credit rating is applied to government and enterprise. A high credit rating means the entity can fully payback its loan in high possibility. A low credit rating means current financial condition of the entity is not good or the entity has a bad history on repaying its debt and indicate a high possibility of default. Credit rating of an entity can determine if the entity will get a loan, interest rate of the loan and some favorite items in agreement.

Credit rating is very important. Credit rating of borrower is determined by the information that credit agency collected including current financial condition and entity's ability to pay back its debt. Borrowing history and economic potential of the entity is important in rating process. Any missed payment or defaults on loans negatively impact the rating. If the entity owns a positive economic outlook, its rating tends to be higher. Otherwise, its credit rating will fall.

The United States was the first country to appear in a credit rating. After the credit crisis in the US bond market in 1929, services that provided borrower's repayment ability and credit quality in financial market began to appear. Different levels of credit risk were represented by letter-level symbols. Subsequently, credit analysis methods continued to improve, and rating agencies began to use statistical methods and mathematical models to assess the borrower's possibility of default and future creditworthiness.

A scientific and reasonable credit rating can reflect the borrower's future default and credit ability. Credit rating can also help investors or lenders understand the risk of investing and make appropriate choices.

2.2 Credit Rating Method

With the developing of credit rating, the method used to measure credit risk is constantly evolving. The methods start from expert analysis to credit scoring model and now possibility of default model. It is a method for commercial banks to distinguish and measure credit risk of funds. Credit rating plays an important role for banks in credit risk management. The traditional rating methods used commonly are the expert analysis method and the credit scoring method and these methods are used to estimate credit risk of corporates before credit risk occurs. Usually, the rating process occurs before banks make loans. The new rating method is the probability of default model. This method is usually used to analyze credit events and collect data.

Expert analysis method can also be called the expert system. This is a system used to measure credit risk of borrowers according to the evaluation of kinds of important factors based on experience, skills and professional knowledge of experts. The expert analysis method mainly analyzes two types of factors to analyze credit of the borrowers: factors related to the market and factors related to the borrower. Economic cycles, interest rate, and macroeconomic policies are market-related factors. Leverage, volatility of return and reputation are factors associated with borrowers.

The credit scoring model is a quantitative model of traditional credit risk. It investigates various characteristics of the borrower and quantifies the results and use numbers to represent the borrower's credit ability, and accordingly determines the corresponding credit rating for the borrower. It is commonly used by commercial banks to evaluate corporate credit. It is a model built based on simulating historical data. This method owns obvious advantages: the rating results have good consistency; the use is convenient; and the operability is strong. However, there is a demand for historical data. The model pays too much attention on analyzing of historical data and lack the ability to distinguish the environment and the changes of the economy in future, and the size of the enterprise's probability of default cannot be accurately measured.

The default probability model is a modern credit risk assessment method. It can directly measure the customer's default level. However, the requirements for historical data are correspondingly higher. Banks should clearly and consistently define defaults and accumulate enough historical data.

2.3 Credit Rating Industry

Credit rating has a history around 100 years since *Moody's Analysis of Railroad Investment* (John Moody, 1909, U.S.A) was published which announced the birth of credit rating industry.

The United States is one of the earliest countries that start credit rating business. After the economic crisis in 1929, the importance of credit rating was noticed, and an effective and scientific credit rating process was started to be establish. Since the Securities Law was issued in 1933, the rating industry in the United States has begun to flourish. Other developed countries such as the United Kingdom, Japan, Canada and other countries began to set up credit rating agencies in the 1970s. The credit rating industry in some developing countries began in the 1980s, such as the Philippines (1982), South Korea (1985), and India (1988).

Many credit rating agencies have emerged, and they can be roughly divided into two types. One is credit rating agencies focus on the capital market, and their rating targets are the state, banks, securities companies and listed companies. Another is credit rating agencies for SMEs.

2.3.1 Credit Rating Industry in China

The first credit rating agency of China was established in 1987. At the end of 1990, 96 credit rating agencies had been established. Due to high inflation, the PBC’s head office canceled the bank’s internal rating and established the National Credit Rating Committee to carry out the rating business.

In the 1990s, rating agencies were established, such as Shanghai New Century (1992.07), China Chengxin (1992.10), Dagong International (1994), etc. The rating business is relatively narrow and limited in rating of loan companies and corporate bonds.

In 1997, the People's Bank of China initially determined the qualifications of nine credit rating agencies for credit rating of corporate bonds.

From 2000 to 2004, the type of bonds has increased in the bond market, and the regulatory authorities make use of credit rating results and the market demand for credit ratings was increased.

Since 2005, the credit rating agencies have well developed. Leaders of this industry begun to appear. There are more than 100 credit rating agencies, and five of them have begun to take shape, Joint Credit, China Chengxin, Dagong International, Shanghai New Century, Shanghai Far East;

Both the subject rating and the bond rating category in the credit market have increased significantly. For example, in addition to the rating of the borrowing company, there is the rating of the bonding company. The credit rating is applied on various bills such as corporate bonds, short-term financing bills, convertible bonds, financial bonds. Domestic rating agencies cooperate with international rating agencies. In 2005, the Joint Credit cooperate with Fitch. In 2006, Moody's purchased a 49% stock of China Chengxin.

2.3.2 Big Three Credit Rating Agencies

The global credit rating industry is highly concentrated with three agencies – Moody's, Standard & Poor's and Fitch – controlling nearly the entire market.

Moody's Investors Service

John Moody and Company first published "Moody's Manual" which provided basic statistics and general information about stocks and bonds of various industries in 1900. From 1903 until the stock market crash of 1907, "Moody's Manual" was a national publication. In 1909 Moody began publishing "Moody's Analyses of Railroad Investments," which added analytical information about the value of securities and announced the birth of credit rating industry. Expanding this idea led to the 1914 creation of Moody's Investors Service, which, in the following 10 years, would provide ratings for nearly all the government bond markets at the time. By the 1970s Moody's had been rating commercial paper and bank deposits, becoming the full-scale rating agency that it is today.

Standard & Poor's

Henry Varnum Poor first published the "History of Railroads and Canals in the United States" in 1860. The forerunner of securities analysis and reporting to be developed over the next century. Standard Statistics formed in 1906, which published corporate bond, sovereign debt and municipal bond ratings. Standard Statistics merged with Poor's Publishing in 1941 to form Standard and Poor's Corporation, which was acquired by The McGraw-Hill Companies Inc in 1966. Standard and Poor's has become best known by indexes such as the S&P 500, a stock market index that is both a tool for investor analysis and decision-making and a U.S. economic indicator.

Fitch Ratings

John Knowles Fitch founded the Fitch Publishing Company in 1913, providing financial statistics for use in the investment industry via "The Fitch Stock and Bond Manual" and "The

Fitch Bond Book". In 1924, Fitch introduced the AAA through D rating system that has become the basis for ratings throughout the industry. With plans to become a full-service global rating agency, in the late 1990s Fitch merged with IBCA of London, subsidiary of FIMALAC, S.A., a French holding company. Fitch also acquired market competitors Thomson BankWatch and Duff & Phelps Credit Ratings Co. Beginning in 2004, Fitch began to develop operating subsidiaries specializing in enterprise risk management, data services and finance-industry training with the acquisition of a Canadian company, Algorithmics, and the creation of Fitch Solutions and Fitch Training.

2.4 Small and Medium Enterprises

By the end of 2017, the number of SMEs in China reached 27.263 million, and the contribution of SMEs to the national fiscal revenue accounted for more than 50%. SMEs' contribution to GDP, fixed assets investment and external direct investment accounted for more than 60%. Technological innovation and new products from SMEs accounted for more than 70%. SMEs provides position for more than 80% urban employees. Contribution of SMEs to new employment accounted for more than 90%.[1]

On industry, SMEs in manufacturing industry takes up more than 90% of total SMEs. There are 31 sectors in manufacturing industry and 9 of them take up more than 5% of the industry. On another word, manufacturing industry takes an important part of SMEs.

Made in China 2025 was announced in 2015 and focus on to reduce China's reliance on foreign technology imports and encourage manufacturing industry to transform. There is a huge demand on funds for these SMEs.

[1]Speech by Ma Peihua, Vice Chairman of the 12th National Committee of the Chinese People's Political Consultative Conference at the Opening Ceremony of the 2018 World Small and Medium Enterprises Conference

The definition of Small and Medium Enterprises is relative and vague. There are no unified standards that accepted all over the world. The main reason is that economic level and economic environment is different in countries and areas. It’s impossible to give standard that suits every counties and areas. The developing of enterprise is dynamic and complex and it is influenced by many factors and conditions. It is impossible to find a standard that includes them all.

Generally, there are three indicators that used to distinguish scale of enterprises: assets, revenue and number of employees. There are different standards for SMEs in different countries. In the European Union, a small-sized enterprise is a company with fewer than 50 employees while a medium-sized enterprise is one with fewer than 250 employees. In addition to small and mid-size companies, there are micro-companies which employ up to 10 employees.

In China, the standard for SMEs has changed several times. At the end of 2017, 《*Statistical methods for the division of large, medium and small micro enterprises*》 (2017) was issued by National Bureau of Statistics of China. The division of enterprises is determined annually by the government's comprehensive statistical department based on the statistical annual report. According to industry categories, major categories, medium categories and combination categories, China's enterprises are divided into four types: large, medium, small and micro enterprises according to the number of employees, revenue, assets or other surrogate indicators. Take manufacturing industry as example, number of employees of SMEs should lower than 1000 but higher than 20 and revenue should lower than 400 million CNY but higher than 3 million CNY.

The difference between large enterprises and SMEs is not only reflected in the scale, but also in terms of organizational structure and management methods. These differences will also be reflected in finance. SMEs have their own unique characteristics. These characteristics not only indicate the advantages of SMEs compared with large enterprises, but also reflect the disadvantages of SMEs.

The most important characteristics of SMEs are small scale and high flexibility of operation. The small scale of enterprise is reflected in the average number of employees and average sales. This feature also determines that SMEs have inevitable disadvantages in market competition, such as: single product service, poor ability to withstand risks, inadequate internal control system, and imperfect management system.

In the management structure of SMEs are characterized by a high degree of unification of possession and management, which means a lower agency costs; SMEs that focus on entrepreneurs' individual decisions lead to low efficiency in organization and decision-making mechanisms directly. The transparency of decision-making is also low, and SMEs have a disadvantage in imperfect checks and balances. At the same time, due to these characteristics of the management structure, SMEs can enhance the resilience and speed of the enterprise on the other hand; SMEs are generally unsatisfactory in terms of market and resource occupancy, have low market share, have strong product substitution and anti-risk ability is weak.

The financial characteristics of SMEs are quite different from those of large enterprises, mainly reflecting the financing method. Due to its short set-up time and poor information transparency, it is difficult for external investors to obtain accounting information such as required credit records and standardized financial statements while their SMEs have poor credit guarantee capabilities and lack fixed assets can be used for mortgage loans. These reasons have accumulated to restrict the access of SMEs to external financing. Second, the business characteristics of SMEs determine the financial characteristics of SMEs. Operational flexibility is the foundation of SMEs in the market competition. It must require enterprises have quick capital turnover, invest less in fixed assets, and use more current assets and short-term liabilities. The low-income investment of SMEs, which is highly dependent on current assets and short-term debt, is a financial reflection of its operating characteristics.

2.5 Credit Rating of SMEs in China

The implementation of credit rating for SMEs is conducive to SMEs entering the capital market and broadening the scope of financing, reducing financing costs. SMEs that have been assessed by credit rating agencies and earn credit ratings can enable investors and financial institutions to clearly understand their own characteristics and advantages, which will help increase the visibility and credibility of the company and enable it to find suitable Financial institutions facilitate their access to capital markets and expand the scope of financing.

The credit rating of SMEs with the willingness to lend provides convenience for banks to lend to SMEs, assists banks in preventing risks, and reduces the financing costs of SMEs, which helps to form a virtuous circle of bank loans to SMEs.

There is no clear and unified laws and regulations specifically targeting SMEs' credit ratings. As a result, the credit rating behaviors and rating results of SMEs are not effectively protected by law.

Generally, China's credit legislation is still not perfect. The government has not yet issued clear policies and regulations for the credit industry. There is no legal basis for the collection and use of integrity data, the management of the evaluation industry, and the use of credit ratings.

First, there are many legal gaps and it is hard for government or financial institutions to collect credit information for SMEs. Since there is no clear and unified law to regulate the market price of SME credit data, it is difficult for financial institutions to grasp the market price of credit data. This is an important reason for the high credit information of SMEs in China.

Secondly, the lack of legal supervision in the credit evaluation industry and no corresponding legal regulation on the number and quality of employees in credit rating management. Chinese SMEs credit evaluation industry has the contradiction between lack of talent and insufficient supervision. The lack of the above-mentioned laws leads to the low threshold for the credit information market to enter, which makes China's credit rating agencies appear to have fewer employees, uneven quality, and college education. As a result, the phenomenon of the collection of integrity data is backward, the collection cost increases, and the credibility of the rating information provided by the company decreases. Coupled with the commercial credit risk caused by information asymmetry, the development of China's SMEs is struggling.

Third, China's SME credit evaluation agencies belong to social intermediaries. They do not have the administrative power to force enterprises to conduct credit evaluation. Many SMEs have poor credit concepts. They only pursue more profits, expect short-term benefits, and actively participate in credit. The awareness of rating is weak, and some SMEs even use the lack of legal norms to deliberately escape bank loans and default on corporate loans. This is very unfavorable for punishing the behavior of the untrustworthy and maintaining the rights and interests of the trustworthy. Thus further contributing to the arrogance of the untrustworthy behavior of the SMEs and making them more ignorant of the existence of credit for their own benefit. Unsound laws and regulations make companies that operate unfairly not get the punishments that the law should have, so that credit evaluation agencies lose their trust in the face of business needs and lose market demand.

3. Description of Theoretical Background and Selected Models

In order to analysis credit risk of companies, quantitative analysis was used to find financial condition of companies which means there are a lot of financial ratios used. Concept of these financial ratios is explained in this part.

Based on financial condition of companies, companies should be divided into different groups. Different groups of companies own different credit risk levels and further analysis will take to find credit risk measuring models.

And many analysis methods and test methods used in this thesis. In this part, these methods are introduced.

3.1 Concept of Financial Ratios

When it comes to quantitative analysis, financial ratio analysis helps us work with data in financial statement in an organized way.

3.1.1 Liquidity Ratio

Current ratio. It is the ratio of current assets to current liabilities. It measures the obligation of the company to satisfy its current liabilities with current assets. When the current ratio is 1, it means the book value of current assets and liabilities is equal. This index is used to reflect company's debt-paying ability in the short-term. The higher is the ratio, the higher is level of liquidity of the company's assets.

$$\textit{Current ratio} = \frac{current\ assets}{current\ liabilities} \tag{3. 1}$$

Quick ratio. It is the ratio of quick assets and current liabilities. Generally, Quick assets include those current assets that can be quickly converted to cash at close to their book values such as cash, cash equivalent, marketable securities and account receivable. It reflects the ability of a company to use its quick assets to pay for its current liabilities immediately. If the ratio of a company is less than 1, it means the company doesn't have the ability to pay back its current liabilities fully. The best ratio is 1.0-1.5 to companies.

$$\textit{Quick ratio} = \frac{cash\ and\ equivalent + marketable\ securities + account\ receivable}{current\ liability} \quad (3.2)$$

Short-term debt to total liability ratio. It indicates the extent of a firm's reliance on short-term financing. Companies that rely on short term funds are more sensitive to liquidity shocks than those with longer-term debt finance as debt facilities can be withdrawn immediately. General manufacturing industries have far greater exposure to short term debt where it typically accounts for more than two thirds of their total debt.

$$\textit{Short-term debt to total liability ratio} = \frac{short-term\ debt}{total\ liability} \quad (3.3)$$

Long-term debt-to-assets ratio. It is the ratio of long-term debt and total assets. It indicates the percentage of the company's assets financed with long-term debt. When it was used to calculate the company's financial leverage, the debt usually includes only the long-term debts. The higher this ratio is, the lower liquidity and weaker solvency the company owns. It also means that the company is more dependent on debt when it grows its business.

$$\textit{Long-term debt-to-assets ratio} = \frac{long-term\ debt}{total\ assets} \quad (3.4)$$

3.1.2 Profitability Ratio

Gross margin. It is the ratio between revenue and revenue minus its cost of goods sold (COGS). It reflects the as a percentage of difference between selling price and cost on a per-unit basis. It is used to determine the value of incremental sales, and to guide pricing and promotion decision.

$$\textit{Gross margin} = \frac{gross\ revenue}{revenue} \quad (3.5)$$

Operating margin. It is the ratio of operating income and revenue. In business, it is also known as operating income margin and operating profit margin. It uses to measure how much operating income can be brought by each dollar of premium and it can reflect the underwriting results of a company. This ratio should be higher than 0.

$$\textit{Operating margin} = \frac{operating\ income}{revenue} \times 100\% \tag{3. 6}$$

Net margin. It is the ratio of net profit and revenue. This ratio can reflect the profit level of a company in a certain period. It can also be used to compare the management level during different periods to improve the economic benefits of the company.

$$\textit{Profit margin} = \frac{net\ income}{revenue} \times 100\% \tag{3. 7}$$

Return on assets (ROA). It is the ratio of net income and average total assets. It reflects the percentage of how profitable a company's assets are in generating revenue. Return on assets gives an indication of the capital intensity of the company, which will depend on the industry. Companyies that require large initial investments will generally have lower return on assets.

$$\textit{Return on assets} = \frac{net\ income}{average\ total\ assetts} \times 100\% \tag{3. 8}$$

Return on equity (ROE). It is the ratio of earning after tax and equity. It reflects the amount of return earned on the shareholders' equity invested. It is usually used by investors to evaluate current and prospective business investments. This ratio can be improved when a company purchases its own stock back from an investor or uses more debt and less equity to fund its operations.

$$\textit{Return on equity} = \frac{earning\ after\ tax}{equity} \tag{3. 9}$$

Return on invested capital (ROIC). It is the ratio of earnings before interest and taxes (EBIT), taxes and invested capital. It is a ratio used in finance, valuation and accounting, as a measure of the profitability and value-creating potential of companies after considering the amount of initial capital invested.

$$ROIC = \frac{net\ income - dividends}{total\ capital} \tag{3. 10}$$

3.1.3 Operating Performance Ratio

Free cash flow to net income. It is the ratio of free cash flow divided by net income. This ratio reflects the relationship between free cash flow and net income. Free cash flow and net income are similar measures of company's earnings, but free cash flow comes from cash flow statement and net income comes from income Statement.

$$Free\ cash\ flow\ to\ net\ income = \frac{free\ cash\ flow}{net\ income} \tag{3. 11}$$

Days Inventory Outstanding (DIO). It is the ratio of total inventory and cost of goods sold. This ratio indicates the average time in days that a company takes to turn its inventory, including goods that are a work in progress, into sales. Usually, a smaller number is preferred. A smaller number indicates that a company is more efficiently and frequently selling off its inventory, which means rapid turnover leading to potential for higher profits (assuming that sales are being made in profit). On the other hand, a large DIO indicates the company may be struggling with obsolete, high-volume inventory and may have invested too much into the same.

$$Days\ inventory\ outstanding = \frac{total\ inventory}{cost\ of\ goods\ sold} \tag{3. 12}$$

Receivable turnover ratio. This ratio is called debtor's turnover ratio as well. It is the ratio of average net receivables and net receivable sales. It reflects the average number of company's accounts receivable turning to cash. It is an accounting measure used to measure how effective a company is in extending credit as well as collecting debts. The receivables turnover ratio is an activity ratio, measuring how efficiently a firm uses its assets. The days of receivable turnover is influenced by the company's credit policy. The close is the days to credit period, the better it if for the company.

$$\textit{Receivable turnover ratio} = \frac{total\ ravenue}{average\ net\ receviables} \tag{3. 13}$$

Inventory turnover. It is the ratio of total revenue and average inventory. It reflects how many times a company's inventory is sold and replaced in a certain period such as a year. When this ratio of a company is low, it means the company is selling its goods inefficiently. It also means the company purchases too much inventory for demand and this may lead to that the company sells its goods in discount.

$$\textit{Inventory turnover} = \frac{total\ revenue}{average\ inventory} \tag{3. 14}$$

Fixed-asset turnover. It is the ratio of total revenue and total fixed-assets. A fixed asset is any tangible piece of property and can be used over the long term, which a company owns and uses in its general operations. It is also known as capital assets and property, plant, and equipment (PP&E). This ratio aims to measure how productive a company's fixed assets are when it comes to generating sales. The higher that the yearly turnover rate on assets is, the better the company is at managing them and using them to generate sales.

$$\textit{Fixed-assets turnover} = \frac{total\ revenue}{total\ fixed{-}assets} \tag{3. 15}$$

Assets turnover. It is the ratio of total revenue and total assets. It reflects the efficiency of a company's use of its assets in generating sales revenue or sales income to the company.

Companies with low profit margins tend to have high asset turnover, while those with high profit margins have low asset turnover. Companies in the retail industry tend to have a very high turnover ratio due mainly to cutthroat and competitive pricing.

$$\textit{Assets turnover} = \frac{total\ revenue}{total\ assets} \tag{3. 16}$$

Payable period. It indicates the average time (in days) that a company takes to pay its bills and tells how well the company's cash outflows are being managed. A company with a higher payable period takes longer to pay its bills, which means that it retains the available funds for a longer duration. It may allow the company an opportunity to utilize the available cash in a better way to maximize the benefits.

$$\textit{Days inventory outstanding} = \frac{account\ payable}{cost\ of\ goods\ sold} * 365 \tag{3. 17}$$

3.1.4 Capital Structure Ratio

Equity multiplier. It is the ratio of total assets to equity. It is a measure of financial leverage. Companies finance their operations with equity or debt, so a higher equity multiplier indicates a larger portion of asset financing is attributed to debt and higher risk.

$$\textit{Equity multiplier} = \frac{total\ assets}{total\ equity} \tag{3. 18}$$

Debt-to-equity. It is the ratio of total liabilities to total shareholder's equity. It reflects the relationship of capital provided by creditors and capital provided by investors or shareholders. It can measure if the basic financial structure of financial company is stable and indicates how much the capital of creditors and investors is ensured by shareholders' equity. When this ratio is high, it means the debt capital is high in total capital, so the guarantee degree of debt capital is weak. In other words, the debt paying ability of the company is weak.

$$Debt\ to\ equity = \frac{total\ debts}{total\ shareholders'equity} \tag{3. 19}$$

Debt to assets. It is the ratio of total liabilities and total assets. It reflects how much assets are raised by borrowing in the total assets and it can also be used to measure the degree of safety for a creditor to loan. The index is a comprehensive index to evaluate liabilities level of a company. Company with high debt ratio is said to be highly leveraged. The higher is the ratio, the greater risk is associated with the operation of the company. When the debt to assets ratio is 100% or higher than 100%, it means the company owns no assets or the company is insolvency.

$$Debt\ to\ assets = \frac{total\ liabilities}{total\ assets} \tag{3. 20}$$

3.1.5 Altman Z-score

The Altman Z-Score is a formula of 5 basic financial ratios to help determine the financial health of a company. It is a probabilistic model to screen for bankruptcy risk of a company.

Studies show that the Z-Score can predict 80-90% of bankruptcies 1 year prior to the fact. It does this with a small percentage of false positives. In other words, the formula provides high confidence probabilities but not certainty.

Other studies show that there is great value in evaluating the strength of balance sheets. Stocks of companies with weak balance sheets underperform the market often. This makes the Altman Z-Score a great tool to quickly screen the health of a balance sheet.

In this thesis, the companies chosen are listed Chinese SMEs in manufacturing industry. There is a Z-score formula designed for manufacturing industry:

$$Z\text{-}Score = 1.2(A) + 1.4(B) + 3.3(C) + 0.6(D) + 1.0(E) \tag{3. 21}$$

Where:

A = Working Capital (Current Assets – Current Assets) / Total Assets (Measures liquidity *of firm)*

B= Retained Earnings / Total Assets (measures accumulated profits compared to assets)

C= Earnings Before Interest & Taxes (EBIT) / Total Assets (measures how much profit the firm's assets are producing)

D= Market Value of Equity (Mkt. Cap. + Preferred Stock) / Total Liabilities (compares the company's value versus its liabilities)

E= Sales / Total Assets (efficiency ratio – measures how much the company's assets are producing in sales).

When result of Z-Score is lower than 1.81, it represents the company is in distress which means higher risk. When result of Z-Score is between 1.81 and 2.99, it represents the company is in "caution" zone which means there is a risk but not so high. When result of Z-Score is higher than 2.99, it represents the company owns a safe balance sheet.

In this thesis, Z-score helps to divide companies in to groups to analyze the companies.

3.2 Cluster Analysis

Cluster analysis is a class of techniques that are used to classify objects or cases into relative groups called clusters. Cluster analysis is also called classification analysis or numerical taxonomy. In cluster analysis, there is no prior information about the group or cluster membership for any of the objects.

Cluster Analysis has been used in marketing for various purposes. Segmentation of consumers in cluster analysis is used based on benefits sought from the purchase of the product. It can be used to identify homogeneous groups of buyers.

Cluster analysis involves formulating a problem, selecting a distance measure, selecting a clustering procedure, deciding the number of clusters, interpreting the profile clusters and finally, assessing the validity of clustering.

The variables on which the cluster analysis is to be done should be selected by keeping past research in mind. It should also be selected by theory, the hypotheses being tested, and the judgment of the researcher. An appropriate measure of distance or similarity should be selected. The most commonly used measure is the Euclidean distance or its square.

Clustering procedures in cluster analysis may be hierarchical, non-hierarchical, or a two-step procedure. A hierarchical procedure in cluster analysis is characterized by the development of a tree like structure. A hierarchical procedure can be agglomerative or divisive. Agglomerative methods in cluster analysis consist of linkage methods, variance methods, and centroid methods. Linkage methods in cluster analysis are comprised of single linkage, complete linkage, and average linkage.

The non-hierarchical methods in cluster analysis are frequently referred to as K means clustering. The two-step procedure can automatically determine the optimal number of clusters by comparing the values of model choice criteria across different clustering solutions. The choice of clustering procedure and the choice of distance measure are interrelated. The relative sizes of clusters in cluster analysis should be meaningful. The clusters should be interpreted in terms of cluster centroids.

The splitting method is used in this thesis and this method is also called Partitioning method. In this method, k partitions are created. The number of partitions to be created is k. Then a loop positioning technique is used to help improve the partition quality by moving objects from one partition to another.

Typical Partitioning method including k-means, k-medoids, CLARA (Clustering LARge Application), CLARANS (Clustering Large Application based upon RANdomized Search), and FCM method.

k-medoids method was applied in later analysis. K decide number of clusters we created. The system finds center point of cluster randomly and through iteration process divided observations into groups with closed medians to find clusters. In this cluster method, some extreme value influence result heavily. All the variables are standardized to eliminate this impact.

3.3 Factor Analysis

While creating model with financial ratios, the relationship between the ratios can influence the final model. Relationship between financial ratios are significantly strong. To remove this influence, factor analysis was chosen.

Factor analysis is a multivariate statistical analysis method that studies how to condense many original variables into a few factor variables with minimal information loss and how to make the factor variables have strong interpretability.

Factor analysis refers to transfer variables with overlapped information and correlated variables into several common factors that not correlated. The basic ideal is grouping variables according to correlation between variables and make sure variables in same group has higher relationship and in different groups have lower relationship. Every group represent a common factor.

This method uses a few common factors to explain the complex relationships existing in more than one observed variable. It is not a recombination of the original variables, but a decomposition of the original variables into two parts: the common factor and the special factor. The common factor is a few factors common to all variables. The special factor is the factor that each original variable has on its own. Principal factors can be more interpretable after rotation.

3.3.1 Variables Selection

To select variables which suit factor analysis better, Kaiser-Meyer-Olkin (KMO) test was taken on all standardized financial ratios. KMO test is used to compare simple correlation coefficients and partial correlation coefficients between variables. Value of KMO statistic is between 0 and 1.

When the sum of squares of the simple correlation coefficients between all variables is much larger than the sum of squares of the partial correlation coefficients, the closer the KMO value is to 1, the stronger the correlation between the variables, the more suitable the original variables are for factor analysis. When the sum of the squares of the simple correlation coefficients is close to 0, the closer the KMO value is to 0, the weaker the correlation between the variables, and the more unsuitable are the original variables to be used in factor analysis.

While selecting proper variables for factor analysis, variables with KMO value higher than 0.5 can be used in factor analysis. The higher is KMO value, more suitable is the variable for factor analysis.

3.3.2 Model of Factor Analysis

There are a set of observable random variables $X=(X_1, X_2, X_3, \cdots, X_p)$ with $E(X)=0$

A set of unobservable variables $F=(F_1, F_2, F_3, \cdots, F_m)$ $(m<p)$ with $E(F)=0$ and covariance of common facor $Cov(F)=I$ which means factor F are not correlated.

Unobserved stochastic error terms $\varepsilon=(\varepsilon_1, \varepsilon_2, \varepsilon_3, \ldots, \varepsilon_p)$ with $E(\varepsilon)=0$ and ε are not correlated, F and ε are not correlated.

The model for factor analysis is:

$$
\begin{aligned}
X_1 &= a_{11}F_1 + a_{12}F_2 + \ldots + a_{1m}F_m + \varepsilon_1 \\
X_2 &= a_{21}F_1 + a_{22}F_2 + \ldots + a_{2m}F_m + \varepsilon_2 \\
&\cdots \\
X_p &= a_{p1}F_1 + a_{p2}F_2 + \ldots + a_{pm}F_m + \varepsilon_p
\end{aligned}
\tag{3. 22}
$$

The model is focus on variables and each factor is orthogonal, so it is also called R-type orthogonal factor model.

The matrix is $X = AF + \varepsilon$

In this model,

The rule $m \leqslant p$ should be obeyed;

Covariance of F and ε is $Cov(F, \varepsilon)=0$, which means F is not correlated with ε;

Variance of F is $D(F)=I_m$, which means $F_1, F_2, F_3, \cdots, F_m$ are not correlated and own same variance.

Special factors $\varepsilon_1, \varepsilon_2, \varepsilon_3, \ldots, \varepsilon_p$ are not correlated and owns different variances.

Common factor is represented by F, they are factors that appear together in the expressions of the various original observed variables and are independent and unobservable theoretical variables.

Special factor is represented by variable ε. It is specially owned by X_i which belongs to vector X.

Matrix A is factor loading matrix and a_{ij} in A is factor load. covariance of X_i and F_j and correlation coefficient of X_i and F_j is represented by a_{ij}. This reflects degree of dependence between X_i and F_j.

There are two statistics in the factor load matrix A that are important: the variable commonality and the variance contribution of the common factor.

The sum of the squares of the elements of the i-th row in the factor load matrix A is denoted as h_i^2, which is called the commonality of the variable X_i. It is the total contribution of common factors to variance of X_i and reflects impact of common factors to variable X_i. the variables have a high degree of dependence on every component of F.

The sum of the squares in the elements of the j-th column in the factor load matrix A is denoted as g_j^2, which is called the variance contribution of the common factor to X. The higher is g_j^2, the higher is contribution of F_j to X. The impact of F_j to X is higher.

3.3.3 Factor Rotation

Aim of creating factor analysis model is not only to find principal factors but also find meaning of every factor to analyze problem in practice. When the representative variables of principle factor are not prominent, factor rotation is needed to find better principle factor.

There are many ways to rotate, and orthogonal rotation and oblique rotation are two types of methods of factor rotation.

Factor rotation is to make the square value of the factor load in the factor load matrix different in the direction of 0 and 1, so that the large load is larger, and the smaller load is smaller. In the process of factor rotation, if the corresponding axes of the factors are orthogonal to each other, it is called orthogonal rotation; if the corresponding axes of the factors are not orthogonal to each other. It is called oblique rotation, and the commonly used oblique rotation method is Promax method.

The most common method is the maximum variance orthogonal rotation method (Varimax) and has been used in this thesis.

3.3.4 Factor Scoring

After the establishment of the factor analysis model, an important function of the factor analysis model is to evaluate the status of each sample in the entire model, which means a comprehensive evaluation. The common factor needs to be expressed by a linear combination of variables.

Assume linear model of common factor *F* is:

$$F_j = u_{j*} x_{j1} + u_{j2*} x_{j2} + \ldots + u_{jp*} x_{jp},\ j=1,\ 2,\ \cdots,\ m \tag{3. 23}$$

This function can be used to calculate score of common factors.

There is other method to estimate score of common factors such as regression estimation, Bartlett estimation, and Thomson estimation.

3.4 Regression Method

3.4.1 Logistic Regression

In statistics, the logistic model is a widely used statistical model developed by statistician David Cox in 1958. In its basic form it uses a logistic function to model a binary dependent variable, although many more complex extensions exist. In regression analysis, logistic regression is estimating the parameters of a logistic model. The function that converts log-odds to probability is the logistic function.

Since 1980, logistic regression analysis has replaced traditional discriminant analysis and become a commonly used method to quantify credit risk of companies. Some assumption of logistic regression suits economic facts and distribution of financial data more. For example, the variables in logistic regression are not required to have linear correlation. It is not required that covariance matrix is equal, and residual should follow normal distribution.

The binary logistic regression model has extensions to more than two levels of the dependent variable: categorical outputs with more than two values are modeled by multinomial regression, and if the multiple categories are ordered, by ordinal logistic regression.

An ordered logistic regression model and the binary logistic regression model was used in this thesis. According to cluster analysis, companies are divided into groups with different credit levels and the level exist order that large number means less risk of default. When companies are divided into two groups, it suits binary logistic regression model.

Relationship of possibility for default and other independent variables is followed:

$$P_i = F(z_i) = \frac{1}{1+e^{-z_i}} \tag{3. 24}$$

$$Z_i = \beta_0 + \beta_1 * X_1 + \ldots + \beta_p * X_p \tag{3. 25}$$

Where possibility of default is represented by P_i. Independent variables are represented by X_i which are financial ratios in this thesis. Coefficient of independent variables is represented by β_i. Value of z belongs to (-∞, +∞).

Possibility for default not occurred is:

$$1-P_i = \frac{1}{1+e^{z_i}} \tag{3. 26}$$

The odds of experiencing default is:

$$\frac{P_i}{1-P_i} = e^{z_i} \tag{3. 27}$$

Use logarithm on both sides:

$$ln(\frac{P}{1-P}) = ln(e^{z_i}) = Z_i = \beta_0 + \beta_1 * X_1 + \ldots + \beta_p * X_p \tag{3. 28}$$

Coefficient of independent variables, coefficient of independent variables, β_i, is estimated with maximum likelihood method. The likelihood function is:

$$L(\beta) = \prod_i^n \pi(X_i)^{Pi}[1-\pi(X_i)]^{1-Pi}, \ i = 1,2,\ldots,n \tag{3. 29}$$

The likelihood function should be maximized to estimate coefficient of independent variables. The differential of coefficient of independent variables for likelihood function will be compute, there will be $n+1$ likelihood function to calculate coefficient of independent variables.

3.4.2 Probit Regression

In statistics, a probit model is a type of regression where the dependent variable can take only two values. The purpose of the model is to Estimate the probability that an observation with characteristics will fall into a specific one of the categories. Moreover, classifying observations based on their predicted probabilities is a type of binary classification model.

A probit model is a popular specification for an ordinal or a binary response model. As such it treats the same set of problems as does logistic regression using similar techniques. The probit model, which employs a probit link function, is most often estimated using the standard maximum likelihood procedure such an estimation being called a probit regression.

In the probit model, the inverse standard normal distribution of the probability is modeled as a linear combination of the predictors.

Probit regression is a special type of the Generalized Linear Models. The bivariate outcome Y follows Bernoulli distribution with parameter p (success probability $p \in (0,1)$). Recall that $E(Y)=p$.

The probit link function:

$$probit(EY)=\Phi-1(p)=\Phi-1(P[Y=1]) \tag{3. 30}$$

This function is used to transform the expectation of this 0/1 dependent variable. Then, the probit of the mean is modelled as a linear combination of the covariates (regressors) X.

A linear function is:

$$probit(EY)=X_i\beta_i, \tag{3. 31}$$

Where β is a vector of unknown parameters. The parameter estimation is based on the maximum likelihood

3.5 Test for Model Created

Shapiro-Wilk Test

Shapiro-Wilk test is a test for normal distribution exhibiting high power, leading to good results even with a small number of observations. In contrast to other comparison tests the

Shapiro-Wilk test is only applicable to check for normality.

The basic idea behind the Shapiro-Wilk test is to estimate the variance of the sample in two ways: the regression line in the QQ-Plot allows to estimate the variance, and the variance of the sample can also be regarded as an estimator of the population variance. Both estimated values should approximately equal in the case of a normal distribution and thus should result in a quotient of close to 1.0. If the quotient is significantly lower than 1.0 then the null hypothesis of having a normal distribution should be rejected.

Kruskal-Wallis Test

The Kruskal Wallis test is the non-parametric alternative to the One-Way ANOVA. Non parametric means that the test doesn't assume your data comes from a particular distribution. The test determines whether the medians of two or more groups are different. Like most statistical tests, a test statistic and compare it to a distribution cut-off point should be calculated. The hypotheses for the test are:

H0: sample medians are equal.

H1: sample medians are not equal.

The Kruskal Wallis test will tell you if there is a significant difference between groups.

There are three assumption for Kruskal Wallis test:

1. The samples drawn from the population are random.
2. Observations are independent of each other.
3. The measurement scale for the dependent variable should be at least ordinal

Wald Test

To find if the model created is correct, the model should be tested. Wald Test was used in this thesis to find if coefficient of independent variables for the whole model are significant. In statistics, the Wald test is one of three classical approaches to hypothesis testing, together with the Lagrange multiplier and the likelihood-ratio test. Then Wald test based on the asymptotic normality of the estimator, specifically in that it tests whether the difference between the unrestricted parameter estimate and the hypothesized value scaled by the unrestricted precision matrix is statistically significant; under the null hypothesis, the test statistic has an asymptotic $\chi 2$-distribution with degrees of freedom equal to the number of restrictions.

$$W=(\theta^{\wedge}/SE\theta)2 \tag{3. 32}$$

The variable W follows $\chi 2$-distribution and it is easy to calculate. A disadvantage is that the estimated standard error of this coefficient will expand, which will cause the Wald statistical value to become very small, when absolute value of coefficient is large.

4. Application on Selected Databases

In this part, financial ratios of observations are analyzed and decided if it is suitable for creating model. Logistic regression is used for model creating with different clusters.

4.1 Data Input and Preprocess

There are data of 205 SMEs and all these enterprises are listed companies. These enterprises are chosen from SME board in Shenzhen Stock Exchange. There are 12 ST companies. “ST” means “Special Treated”. ST companies are those companies that suffers a loss more than consecutive two years or its net capital per share is lower than book value of its stock which means there is a great risk of bankruptcy. ST companies are treated as default companies.

Credit risk of enterprise relates with financial condition of enterprise. In order to find financial condition of enterprises, we choose 20 financial indicators in four type: solvency, profitability, operating performance and capital structure as initial indicators to analyze and help create model. Table 4.1 indicates financial ratios analyzed in this thesis.

Table 4. 1: Origin financial ratios

Solvency	Current ratio	*X1*
	Quick ratio	*X2*
	Current liability to total liability	*X3*
	Long-term liability to total assets	*X4*
Profitability	Gross margin	*X5*
	Operating margin	*X6*
	Net margin%	*X7*
	ROA%	*X8*
	ROE%	*X9*
	Return on invested capital%	*X10*

Operating	Free cash flow to net income	*X11*
	Days inventory	*X12*
	Receivables turnover	*X13*
	Inventory turnover	*X14*
	Fixed assets turnover	*X15*
	Assets turnover	*X16*
	Payable period	*X17*
Capital structure	Equity multiplier	*X18*
	Debt to equity	*X19*
	Debt to assets	*X20*

These financial ratios should be tested to make if there is a significant difference for same ratio in different credit risk levels. Only if there is significant difference between different credit levels, the ratios can be used for further analyzation. The observations should be classified according to their credit risk levels.

While overview data, it can be found that there is big difference between extreme values, mean and standard deviations because of difference in units and magnitude of different variables. The difference has a negative impact on our analysis. Data should be standardized to eliminate this impact and our analysis will go on based on standardized data. Standardized variables are named as $x1 - x20$.

4.1.1 Cluster Analysis

Cluster analysis divides data into different groups and data in same group is similar and dissimilarity between data belongs to different groups.

Whiling using financial ratios *x1-x20* to apply hierarchical method, the result provides groups with small number of observations and this is not good for model creating. Partitioning method was used.

Altman-Z score was used that we divide observations into different groups with different

Z score. Companies with score lower than 1.81 is divided into high risk group and with higher score is safe.

There are 5 clusters divided by different factors

CLA: with factor *x1-x20*, divided into 3 groups 3 is at risk;2 is cautious group; 1 is safe.

CLB: with factor *x1-x20*, divided into 2 groups and 2 means at risk; 1 is safe.

CLZ1: with z, divided into 3 groups 3 is high risk;2 is cautious group; 1 is safe.

CLZ2: with z, divided into 2 groups and 2 means at risk; 1 is safe.

CLZ: with Z, divided into 2 groups and 2 means at risk; 1 is safe.

Table 4.2 introduced number of observations in groups according to clusters.

Table 4. 2: groups divided by cluster

Credit level / Name of cluster	3	2	1
CLA	79	60	16
CLB		88	67
CLZ1	49	62	44
CLZ2		88	67
CLZ		51	104

Following §404 of the Revised Framework from June 2004: A minimum of seven rating classes of non-defaulted borrowers, 7 credit levels should be designed. However, in practice, it appears that only a few observations in a credit level while trying to create 7 and 5 credit level. The model created with small sample can be influenced by some special values. Here we use 3 credit level.

4.1.2 Significant Level

Before use credit level to create model, we should find if the variable follows normal distribution and then decide which method be used to find its significant level.

Shapiro-Wilk (SW) test was used here to test if variables follow normal distribution. Take *x1* as example:

H_0: The sample follows normal distribution

H_1: The sample does not follow normal distribution.

According to information from Table 4.3, W=0.78903, P-value=0. With P-value < α=0.05, H_0 was rejected. This variable doesn't follow normal distribution.

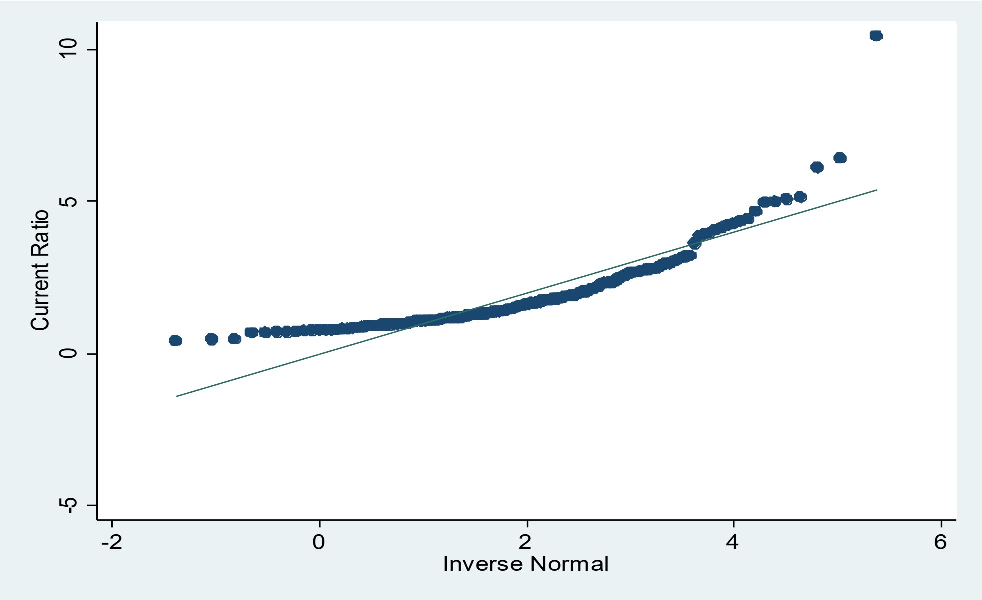
Table 4. 3: Shapiro-Wilk (SW) test on variable X1

```
. swilk X1 in 51/205
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
X1	155	0.78903	25.248	7.332	0.00000

Graph 4. 1: Q-Q plot of variable *x1*



It is also proved by Graph 4.1 above that the variable doesn't follow normal distribution.

All other variables are analyzed by process above and it is proved that no variable follows normal distribution. Nonparametric tests should be used to test if the variable can significantly distinguish observations in different credit risk level.

Kruskal-Wallis test was used and take *x1* in cluster *CLA* which means observations are divided into three groups by k-median method with variable *x1-x20*.

Table 4. 4: Kruskal-Wallis Test on *x1*

```
. kwallis x1, by(CLA)

Kruskal-Wallis equality-of-populations rank test
```

CLA	Obs	Rank Sum
1	16	911.00
2	60	7006.50
3	79	4172.50

```
chi-squared =    73.157 with 2 d.f.
probability =     0.0001

chi-squared with ties =    73.163 with 2 d.f.
probability =     0.0001
```

Hypothesis of Kruskal-Wallis test are:

H_0: distribution of K different groups is the same;

H_1: distribution of K different is not the same

It can be found according to table 4.4 that P-value =0.0001 < α=0.05 and we reject the null hypothesis. Variable *x1* has a significant difference in different group of credit level.

All other variables should be tested to find if its distribution is significant different between different group.

According to correlation analysis between variables, some of them owns significantly strong correlation. It's necessary to make factor analysis.

4.2 Factor Analysis

Because there exists significantly strong relationship between some variables, factor analysis should be used to find common factor and use common factors in logistic regression.

Firstly, Kaiser-Meyer-Olkin (KMO) test was taken to decide variables that suit factor analysis.

Value of KMO statistic is between 0 and 1. Usually, KMO value between 0.6 to 0.7 can be used and if it is lower than 0.5, the variable can't be used in factor analysis.

Table 4. 5: KMO value of standardized financial ratios

Variable	KMO	Variable	KMO	Variable	KMO	Variable	KMO
x1	0.6371	x6	0. 5522	x11	0. 2678	x16	0. 5878
x2	0.6707	x7	0. 7306	x12	0. 5986	x17	0. 5755
x3	0.3905	x8	0. 6994	x13	0. 3401	x18	0. 5709
x4	0.4375	x9	0. 6763	x14	0. 5289	x19	0. 5658
x5	0.5394	x10	0. 7427	x15	0. 7397	x20	0. 7698

Table 4.5 indicate KMO value for variables and there are 4 variables owns KMO value lower than 0.5. Standardized short-term debt to total liability ratio is represented by x3; Standardized long-term debt to assets ratio is represented by x4; Standardized free cash flow to net income is represented by x11; Standardized receivables turnover to total liability ratio is represented by x13. These four variables own KMO value lower than 0.5. As free cash flow is important in manufacturing industry, the standardized free cash flow to net income was kept for later analysis and the other three are deleted.

KMO test was taken again. Variables that own smallest KMO value are delete.

According to test of original variables, we delete 8 variables and analyzing with retained variables.

Analyzing retained variables with factor analysis method with STATA.

According to Graph 4.2 and Table 4.6, the first 3 factors have eigenvalue higher than 1 and these 3 factors explains 98.33% of the information provided by 13 variables. The result of factor extraction is successful. The other 9 factors are not important and will be deleted.

Graph 4. 2: Scree plot of eigenvalues after factor

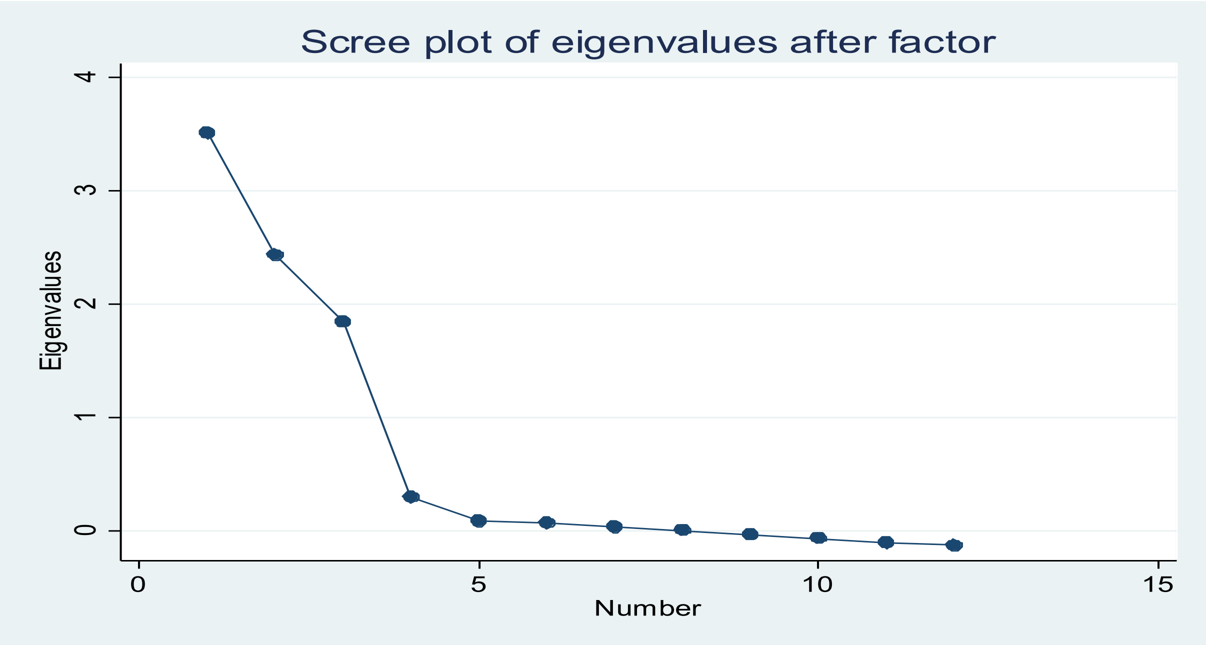


Table 4. 6: Factor analysis on retained variables and the outcome

```
. factor x1-x20 in 51/205
(obs=155)

Factor analysis/correlation                        Number of obs    =       155
    Method: principal factors                      Retained factors =         8
    Rotation: (unrotated)                          Number of params =        66
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.51127	1.07685	0.4432	0.4432
Factor2	2.43442	0.58878	0.3073	0.7504
Factor3	1.84565	1.55189	0.2329	0.9833
Factor4	0.29376	0.21339	0.0371	1.0204
Factor5	0.08037	0.01269	0.0101	1.0306
Factor6	0.06768	0.03924	0.0085	1.0391
Factor7	0.02844	0.02435	0.0036	1.0427
Factor8	0.00409	0.03902	0.0005	1.0432
Factor9	-0.03493	0.03006	-0.0044	1.0388
Factor10	-0.06499	0.04463	-0.0082	1.0306
Factor11	-0.10962	0.02324	-0.0138	1.0168
Factor12	-0.13287	.	-0.0168	1.0000

```
LR test: independent vs. saturated:  chi2(66) = 1663.99 Prob>chi2 = 0.0000
```

Rotate can simplify structure of factors further and it will not influence explanation of factors to original variables. The retained 3 factors will be rotated. Maximum variance orthogonal rotation method is used, and we can get a matrix of factors after maximizing variance.

According to loading matrix in table 4.7, different factors focus on different type of financial ratios and indicate different financial aspects. Take *f1* as example, its load on *x7, x8, x10* is significantly higher than other factors and *x7* is net margin, *x8* is return on assets, and *x10* is return on invested capital. *f1* is focus on profitability of company and named it profitability factor; *f2* focus on operating ability of company and named it operating factor and *f3* focus on solvency and capital structure and named it solvency and structure factor.

Table 4. 7: Factor loading matrix after rotation

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
x1	0.1206	-0.0134	0.9517	0.0794
x2	0.0800	-0.0117	0.9321	0.1247
x5	0.1473	-0.3317	0.3645	0.7354
x7	0.9135	-0.0976	0.1589	0.1307
x8	0.9889	0.0641	0.1081	0.0063
x10	0.9735	0.0567	0.0560	0.0460
x11	0.0129	0.0249	0.1007	0.9891
x14	-0.0163	0.8375	-0.0313	0.2974
x15	0.0334	0.7514	0.0256	0.4336
x16	0.0594	0.9103	-0.0309	0.1669
x17	0.0498	-0.4483	-0.2065	0.7539
x20	-0.3780	-0.0303	-0.6410	0.4453

The value of uniqueness indicate how successfully factor is explain variables. A higher value means variable is not well explained. According to the table above, uniqueness value for *x5, x11, x17* is higher than 0.6 which means they are not successfully explained. The variable *x5* is standardized gross margin; variable *x11* is standardized free cash flow to net income;

variable *x17* is standardized payable period.

According to table 4.8, score of the coefficients was calculated by regression and we can get function of these three common factors:

$f1 = 0.02224*x1 - 0.08433*x2 - 0.00270*x5 + 0.01303*x7 + 1.08495*x8 - 0.06990*x10 - 0.00932*x11 + 0.01216*x14 - 0.01293*x15 - 0.03399*x16 + 0.05325*x17 + 0.04891*x20$

$f2 = 0.04986*x1 + 0.00124*x2 - 0.06388*x5 - 0.27626*x7 + 0.48071*x8 - 0.23836*x10 - 0.01514*x11 + 0.27386*x14 + 0.14251 *x15 + 0.51442 *x16 - 0.05990 *x17 + 0.01463*x20$

$f3 = 0.63491*x1 + 0.31772*x2 + 0.01767*x5 - 0.19648*x7 + 0.45638*x8 - 0.39465*x10 + 0.00060*x11 + 0.02501*x14 - 0.02514 *x15 - 0.01291 *x16 - 0.00124 *x17 - 0.06336*x20$

Table 4. 8: Factor scores

```
. predict f1 f2 f3
(regression scoring assumed)

Scoring coefficients (method = regression; based on varimax rotated factors)
```

Variable	Factor1	Factor2	Factor3
x1	0.02224	0.04986	0.63491
x2	-0.08433	0.00124	0.31772
x5	-0.00270	-0.06388	0.01767
x7	0.01303	-0.27626	-0.19648
x8	1.08495	0.48071	0.45638
x10	-0.06990	-0.23836	-0.39465
x11	-0.00932	-0.01514	0.00060
x14	0.01216	0.27386	0.02501
x15	-0.01293	0.14251	-0.02514
x16	-0.03399	0.51442	-0.01291
x17	0.05325	-0.05990	-0.00124
x20	0.04891	0.01463	-0.06336

The common factors are unrelated according to table 4.9 and this suits requirement of factor analysis that common factors are not correlated.

Table 4. 9: Correlation of common factors

```
. corr f1 f2 f3 in 5/205
(obs=201)

             |       f1       f2       f3
-------------+---------------------------
          f1 |   1.0000
          f2 |   0.0277   1.0000
          f3 |   0.0384  -0.0053   1.0000
```

The common factors are unrelated according to table 4.9 and this suits requirement of factor analysis that common factors are not correlated.

4.3 Logistic Regression

Below we use the *ologit* command to estimate an ordered logistic regression model. We have 5 different clusters based on different variables. These five clusters will be used to create logistic model to classify observations. 155 observations are used while predicting regression model.

4.3.1 Ordered Logit Model

In the first regression model, cluster CLA was used. Companies are divided into 3 groups based on all standardized variables *x1-x20*.

According to table 4.10, Stata fits a null model at iteration 0 which means the intercept-only model. It then moves on to fit the full model and stops the iteration process once the difference in log likelihood between successive iterations become sufficiently small. The final log likelihood (-115.87856) is displayed again. It also tells that 155 observations are used to create this model. The likelihood ratio chi-square of 61.29 with a p-value of 0.0000 tells us that our model is statistically significant, as compared to the null model with no predictors. The pseudo-R-squared at 0.2091 is also given.

Table 4.10 shows the coefficients, standard errors, z-tests and associated p-values, and the 95% confidence interval of the coefficients. All the three common factors are statistically significant.

Table 4. 10: Function from ordered logistic regression for credit risk prediction with CLA

```
. ologit CLA f1 f2 f3

Iteration 0:   log likelihood = -146.52242
Iteration 1:   log likelihood = -122.33484
Iteration 2:   log likelihood = -116.05057
Iteration 3:   log likelihood = -115.87873
Iteration 4:   log likelihood = -115.87856
Iteration 5:   log likelihood = -115.87856

Ordered logistic regression                       Number of obs     =        155
                                                  LR chi2(3)        =      61.29
                                                  Prob > chi2       =     0.0000
Log likelihood = -115.87856                       Pseudo R2         =     0.2091

------------------------------------------------------------------------------
         CLA |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          f1 |  -1.504913   .4047938    -3.72   0.000    -2.298294   -.7115314
          f2 |   1.928339   .4100785     4.70   0.000       1.1246    2.732078
          f3 |  -.7905644   .2003547    -3.95   0.000    -1.183252   -.3978763
-------------+----------------------------------------------------------------
       /cut1 |   -3.16425   .3649865                      -3.87961   -2.448889
       /cut2 |  -.2999653   .2018614                     -.6956064    .0956758
------------------------------------------------------------------------------
Note: 2 observations completely determined.  Standard errors questionable.
```

For *f1*, one-unit increase means 1.50 increase in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

For *f2*, one-unit increase means 1.93 decrease in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

For *f3*, one-unit increase means 0.79 increase in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

The cutpoints shown at the bottom of the output table indicate where the latent variable is cut to make the three groups that we observe in our data. Note that this latent variable is continuous.

In the second ordered logistic regression model, cluster CLZ1 was used. Companies are divided into 3 groups based on standardized variables z.

According to table 4.11 followed, the final log likelihood (-87.508421) is displayed again. The likelihood ratio chi-square of 162.27 with a p-value of 0.0000 tells us that our model is statistically significant, as compared to the null model with no predictors. The pseudo-R-squared of 0.4811 is also given.

Table 4.11 shows the coefficients, standard errors, z-tests and associated p-values, and the 95% confidence interval of the coefficients. The three common factors are statistically significant.

For f1, one-unit increase means 2.40 decrease in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

For f2, one-unit increase means 2.80 decrease in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

For f3, one-unit increase means 2.90 increase in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

Table 4. 11: Function from ordered logistic regression for credit risk prediction with CLZ1

```
. ologit CLZ1 f1 f2 f3 in 51/205,nolog

Ordered logistic regression                       Number of obs   =        155
                                                  LR chi2(3)      =     162.27
                                                  Prob > chi2     =     0.0000
Log likelihood = -87.508421                       Pseudo R2       =     0.4811
```

CLZ1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
f1	-2.404528	.5536688	-4.34	0.000	-3.489699	-1.319357
f2	-2.799907	.4812964	-5.82	0.000	-3.743231	-1.856584
f3	-2.903735	.4375714	-6.64	0.000	-3.761359	-2.04611
/cut1	-1.891635	.3318805			-2.542109	-1.241162
/cut2	2.136608	.3357069			1.478634	2.794581

Note: 2 observations completely determined. Standard errors questionable.

Comparing the two model above, the second model owns smaller absolutely value in log likelihood and higher value of pseudo R^2.

We take the second model as better and take Wald Test on it.

Table 4. 12: Wald Test for ordered logistic regression function on cluster CLZ1

```
. testparm f1 f2 f3 CLZ1

 ( 1)  [CLZ1]f1 = 0
 ( 2)  [CLZ1]f2 = 0
 ( 3)  [CLZ1]f3 = 0

           chi2(  3) =   63.13
         Prob > chi2 =    0.0000
```

Hypothesis of Wald test for the ordered logit function above is:

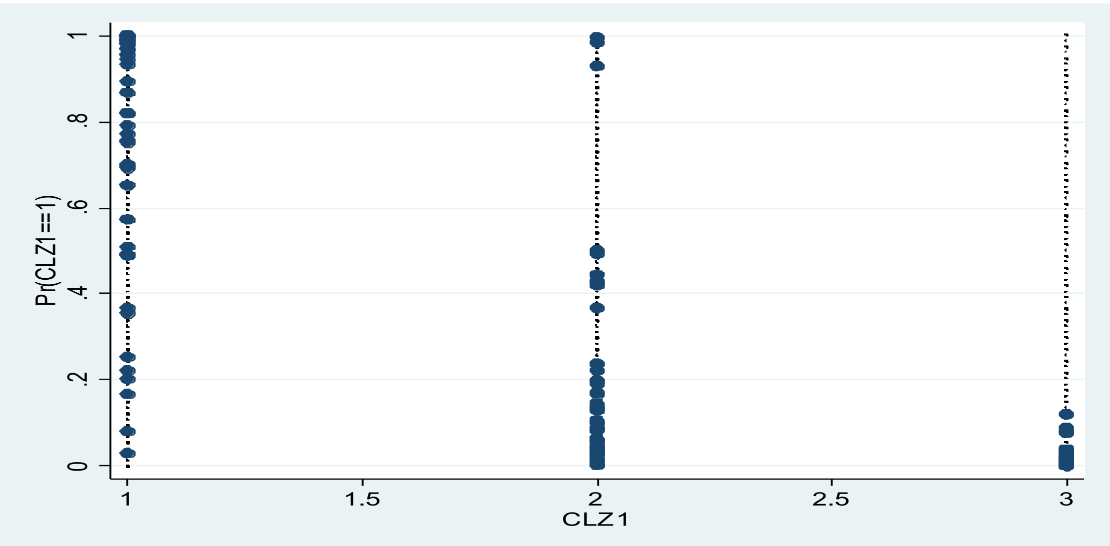
H_0: α_j=0, j=1,2,3;

H_1: $\alpha_1 \neq 0 \vee \alpha_2 \neq 0 \vee \alpha_3 \neq 0$

According to table 4.12, P-value = 0 and is lower than significant level 0.05. We reject H_0 and accept H_1 which means there is at least one parameter in this model does not equal to 0 with a 5% statistical significance.

According to the second model, we predict probability of default for all the observations and these observations are divided into 3 groups according to cluster CLZ1 which is cluster according to standardized Z-score.

Graph 4. 3: Probability of default of observations predicted by the second ologit model



According to graph 4.3, there is a significant difference between CLZ1=1 and the other two, but the other two group are similar. There is a trend that groups with lower probability of default are concentrated in CLZ1= 2 and CLZ1= 3.

4.3.2 Logit Model

This is the third logit regression model, cluster CLB was used. Companies are divided into 2 groups based on all standardized variables x1 to x10. Some change was made for cluster CLB in new cluster B, 0 means safe and 1 means default.

According to the table 4.13 followed, the final log likelihood (-37.344477) is displayed again. The likelihood ratio chi-square of 137.33 with a p-value of 0.0000 tells us that our model is statistically significant, as compared to the null model with no predictors. The pseudo-R-squared of 0.6477 is also given.

Table 4. 13: Function from logistic regression for credit risk prediction with CLB

```
. logit B f1 f2 f3

Iteration 0:   log likelihood = -106.01085
Iteration 1:   log likelihood = -46.150856
Iteration 2:   log likelihood =  -38.18403
Iteration 3:   log likelihood = -37.349047
Iteration 4:   log likelihood = -37.344479
Iteration 5:   log likelihood = -37.344477

Logistic regression                             Number of obs     =        155
                                                LR chi2(3)        =     137.33
                                                Prob > chi2       =     0.0000
Log likelihood = -37.344477                     Pseudo R2         =     0.6477
```

B	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
f1	-4.407806	.9744106	-4.52	0.000	-6.317616	-2.497997
f2	1.431993	.5416218	2.64	0.008	.3704335	2.493552
f3	-5.829231	1.024659	-5.69	0.000	-7.837525	-3.820936
_cons	.0003533	.3180563	0.00	0.999	-.6230257	.6237322

Note: 2 failures and 2 successes completely determined.

The table 4.13 shows the coefficients, standard errors, z-tests and associated p-values, and the 95% confidence interval of the coefficients. The three common factors are statistically significant.

For *f1*, one-unit increase means 4.41 increase in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

For *f2*, one-unit increase means 1.43 decrease in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

For *f3*, one-unit increase means 5.83 increase in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

In this model, constant term owns a P-value at 0.999 which is much higher than significant level 0.05. The constant term is not significant. In this model, we accept the insignificant constant term because it may represent some unobserved effect of financial ratios used.

In the fourth logit regression model, cluster CLZ2 was used. Companies are divided into 2 groups based on standardized variables z. Some change was made for cluster CLZ2 in new cluster Z2, 0 means safe and 1 means default.

According to the table 4.14 followed, the final log likelihood (-45.958646) is displayed again. The likelihood ratio chi-square of 120.10 with a p-value of 0.0000 tells us that our model is statistically significant, as compared to the null model with no predictors. The pseudo-R-squared of 0.5665 is also given.

The table 4.14 shows the coefficients, standard errors, z-tests and associated p-values, and the 95% confidence interval of the coefficients. The three common factors are statistically significant.

For *f1*, one-unit increase means 2.04 decrease in the log odds of being in a higher level of CLZ2 when the other variables in the model are held constant.

For *f2*, one-unit increase means 3.61 decrease in the log odds of being in a higher level of CLZ2 when the other variables in the model are held constant.

For *f3*, one-unit increase means 3.24 decrease in the log odds of being in a higher level of

CLZ2 when the other variables in the model are held constant.

Table 4. 14: Function from logistic regression for credit risk prediction with CLZ2

```
. logit Z2 f1 f2 f3 in 51/205, nolog

Logistic regression                             Number of obs     =        155
                                                LR chi2(3)        =     120.10
                                                Prob > chi2       =     0.0000
Log likelihood = -45.958646                     Pseudo R2         =     0.5665
```

Z2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
f1	-2.037342	.6242189	-3.26	0.001	-3.260789	-.8138953
f2	-3.614374	.7612606	-4.75	0.000	-5.106417	-2.122331
f3	-3.240271	.6251879	-5.18	0.000	-4.465617	-2.014925
_cons	.0551906	.2757458	0.20	0.841	-.4852612	.5956423

Note: 1 failure and 0 successes completely determined.

In this model, constant term owns a P-value at 0.841 which is much higher than significant level 0.05. The constant term is not significant. In this model, we accept the insignificant constant term because it may represent some unobserved effect of financial ratios used.

In the fifth logit regression model, cluster CLZ was used. Companies are divided into 2 groups based on value of Altman Z-score at 1.81. Some change was made for cluster CLZ in new cluster Z0, 0 means safe and 1 means default.

According to the table 4.15 followed, the final log likelihood (-47.648412) is displayed again. The likelihood ratio chi-square of 101.09 with a p-value of 0.0000 tells us that our model is statistically significant, as compared to the null model with no predictors. The pseudo-R-squared of 0.5147 is also given.

Table 4.15 shows the coefficients, standard errors, z-tests and associated p-values, and the 95% confidence interval of the coefficients. The three common factors are statistically significant.

For *f1*, one-unit increase means 1.83 increase in the log odds of being in a higher level of

CLA when the other variables in the model are held constant.

For *f2*, one-unit increase means 2.50 increase in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

For *f3*, one-unit increase means 2.43 increase in the log odds of being in a higher level of CLA when the other variables in the model are held constant.

Table 4. 15: Function from logistic regression for credit risk prediction with CLZ

```
. logit Z0 f1 f2 f3 in 51/205, nolog

Logistic regression                               Number of obs     =        155
                                                  LR chi2(3)        =     101.09
                                                  Prob > chi2       =     0.0000
Log likelihood = -47.648412                       Pseudo R2         =     0.5147
```

Z0	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
f1	1.827573	.6539762	2.79	0.005	.5458032	3.109343
f2	2.495918	.6035166	4.14	0.000	1.313047	3.678789
f3	2.427868	.4664074	5.21	0.000	1.513727	3.34201
_cons	-1.15083	.285583	-4.03	0.000	-1.710562	-.5910974

Note: 0 failures and 1 success completely determined.

Comparing the other three models above, the third model owns smaller absolutely value in log likelihood which is 37.344477 and higher value of pseudo R^2 which is 0.6477. This function is better than the other two within the three function where observations are divided into two groups.

Hypothesis of Wald test for the logit function above is:

H_0: $\alpha_j=0$, j=1,2,3;

H_1: $\alpha_1 \neq 0 \vee \alpha_2 \neq 0 \vee \alpha_3 \neq 0$

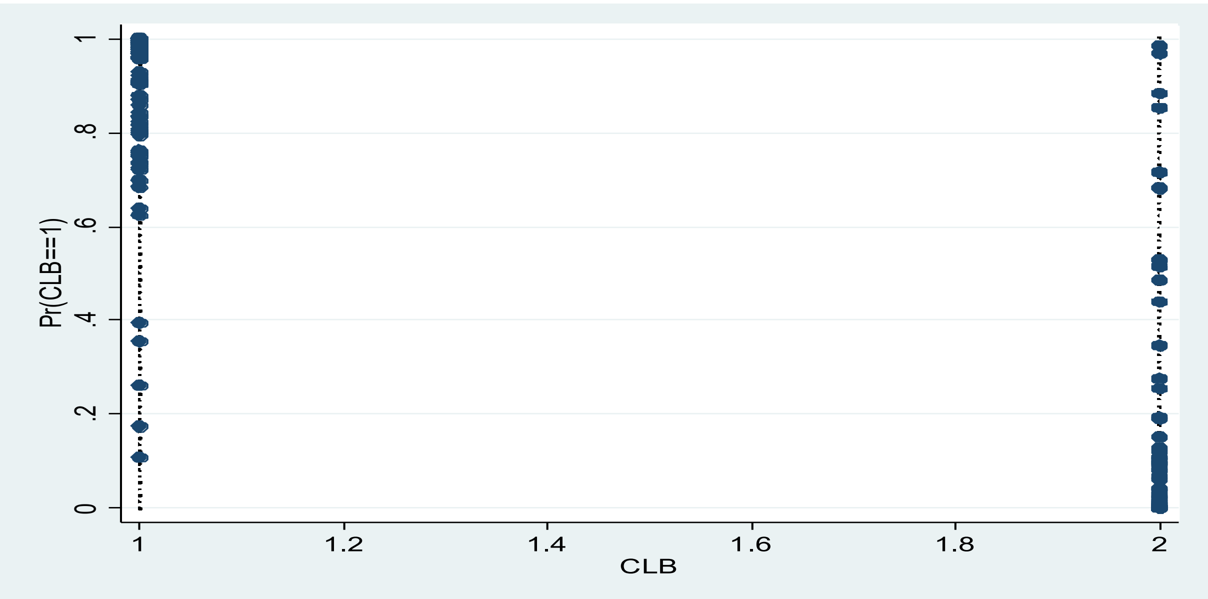
According to the table 4.16, P-value = 0 and is lower than significant level 0.05. We reject H_0 and accept H_1 which means there is at least one parameter in this model does not equal to 0 with a 5% statistical significance.

Table 4. 16:Wald Test for logistic regression function on cluster CLB

```
 ( 1)  [CLB]f1 = 0
 ( 2)  [CLB]f2 = 0
 ( 3)  [CLB]f3 = 0

           chi2(  3) =   32.52
         Prob > chi2 =    0.0000
```

Probability of default for all the observations are predicted according to the third model and these observations are divided into 2 groups according to cluster CLB which is cluster according to all standardized financial ratios.

Graph 4. 4: Probability of default of observations predicted by the third logit model



According to graph 4.4, there is a significant difference between the two groups predicted by the third logit model and observations with lower probability of default concentrated in CLB=2.

4.4 Probit Regression

Probit model is used to model dichotomous or binary outcome variables. In the probit model, the inverse standard normal distribution of the probability is modeled as a linear combination of the predictors. Ordered probit model is also used in this thesis because of clusters with 3 groups.

According to logistic model created, two model will be created in this part with cluster CLB and CLZ1.

4.4.1 Ordered Probit Model

In this model, cluster CLZ1 with 3 credit level is used. Observations are divided into 3 groups based on standardized Altman Z-score.

The likelihood ratio chi-square of 159.51 with a p-value of 0.0000 tells us that our model is statistically significant, that is, it fits significantly better than a model with no predictors.

Table 4. 17: Function from ordered probit regression for credit risk prediction with CLZ1

```
. oprobit CLZ1 f1 f2 f3

Iteration 0:   log likelihood = -168.64502
Iteration 1:   log likelihood = -95.295841
Iteration 2:   log likelihood = -88.940101
Iteration 3:   log likelihood = -88.891529
Iteration 4:   log likelihood = -88.891496
Iteration 5:   log likelihood = -88.891496

Ordered probit regression                         Number of obs   =        155
                                                  LR chi2(3)      =     159.51
                                                  Prob > chi2     =     0.0000
Log likelihood = -88.891496                       Pseudo R2       =     0.4729
```

CLZ1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
f1	-1.20864	.2456597	-4.92	0.000	-1.690125	-.7271564
f2	-1.553186	.2490868	-6.24	0.000	-2.041387	-1.064985
f3	-1.516332	.1907341	-7.95	0.000	-1.890164	-1.1425
/cut1	-1.086538	.173932			-1.427439	-.7456379
/cut2	1.165107	.1726398			.8267394	1.503475

Note: 4 observations completely determined. Standard errors questionable.

In table 4.17, the coefficients, standard errors, the z-statistic, associated p-values, and the 95% confidence interval of the coefficients are indicated. All the three factors are statistically significant according to p-value. The probit regression coefficients give the change in the z-score or probit index for a one unit change in the predictor.

For a one unit increase in *f1*, the z-score decreases by 1.21.

For a one unit increase in *f2*, the z-score decreases by 1.55.

For a one unit increase in *f3*, the z-score increases by 1.52.

Hypothesis of Wald test for ordered probit function above:

H_0: $b_j=0$, j=1,2,3;

H_1: $b_1 \neq 0 \vee b_2 \neq 0 \vee b_3 \neq 0$

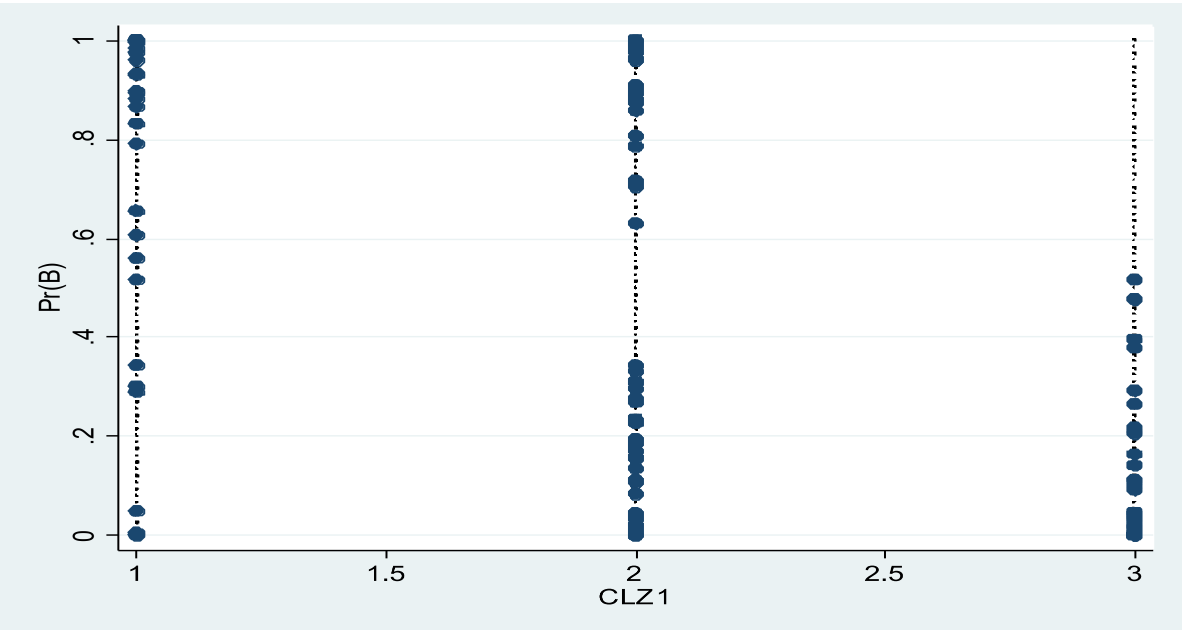
Table 4. 18: Wald Test for ordered probit regression function on cluster CLZ1

```
. testparm f1 f2 f3 CLZ1

 ( 1)   [CLZ1]f1 = 0
 ( 2)   [CLZ1]f2 = 0
 ( 3)   [CLZ1]f3 = 0

           chi2(  3) =   86.01
         Prob > chi2 =    0.0000
```

According to table 4.18 above, P-value = 0 and is lower than significant level 0.05. We reject H_0 and accept H_1 which means there is at least one parameter in this model does not equal to 0 with a 5% statistical significance.

According to the ordered probit model, we predict probability of default for all the observations and these observations are divided into 3 groups according to cluster CLZ1 which is cluster according to standardized Z-score.

Graph 4. 5: Probability of default of observations predicted by the oprobit model



According to graph 4.5, there is a significant difference between CLZ1=1 and CLZ1=3. The group CLZ1=2 owns observations with extreme value on probability of default. This indicate groups in cluster CLZ1 is no significant difference while analyzing by ordered probit model.

4.4.2 Probit Model

To suit probit model, some change was made for cluster CLB with two group. In credit level CLB, 1 represents company is relatively safe and 2 represents high risk of default. In new cluster B, 0 means safe and 1 means default.

Table 4. 19: Function from probit regression for credit risk prediction with CLB

```
. probit B f1 f2 f3

Iteration 0:   log likelihood = -106.01085
Iteration 1:   log likelihood = -46.508552
Iteration 2:   log likelihood = -38.433962
Iteration 3:   log likelihood = -37.837489
Iteration 4:   log likelihood = -37.836694
Iteration 5:   log likelihood = -37.836694

Probit regression                               Number of obs     =        155
                                                LR chi2(3)        =     136.35
                                                Prob > chi2       =     0.0000
Log likelihood = -37.836694                     Pseudo R2         =     0.6431
```

B	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
f1	-2.386597	.5106983	-4.67	0.000	-3.387547	-1.385646
f2	.7574233	.3007405	2.52	0.012	.1679828	1.346864
f3	-3.178394	.4922235	-6.46	0.000	-4.143134	-2.213654
_cons	-.0147726	.1797928	-0.08	0.935	-.3671601	.3376149

Note: 11 failures and 3 successes completely determined.

According to table 4.19, the likelihood ratio chi-square of 136.35 with a p-value of 0.0000 tells us that our model is statistically significant, that is, it fits significantly better than a model with no predictors.

All the three factors are statistically significant with p-value lower than 0.05. The probit regression coefficients give the change in the z-score or probit index for a one unit change in the predictor.

For one unit increase in *f1*, the z-score increases by 2.39;

For one unit increase in *f2*, the z-score decreases by 0.757;

For one unit increase in *f3*, the z-score increases by 3.18.

Take Wald Test on it to exam if parameters are significant:

Hypothesis of Wald test for the ordered probit function above is:

H_0: $b_j=0$, j=1,2,3;

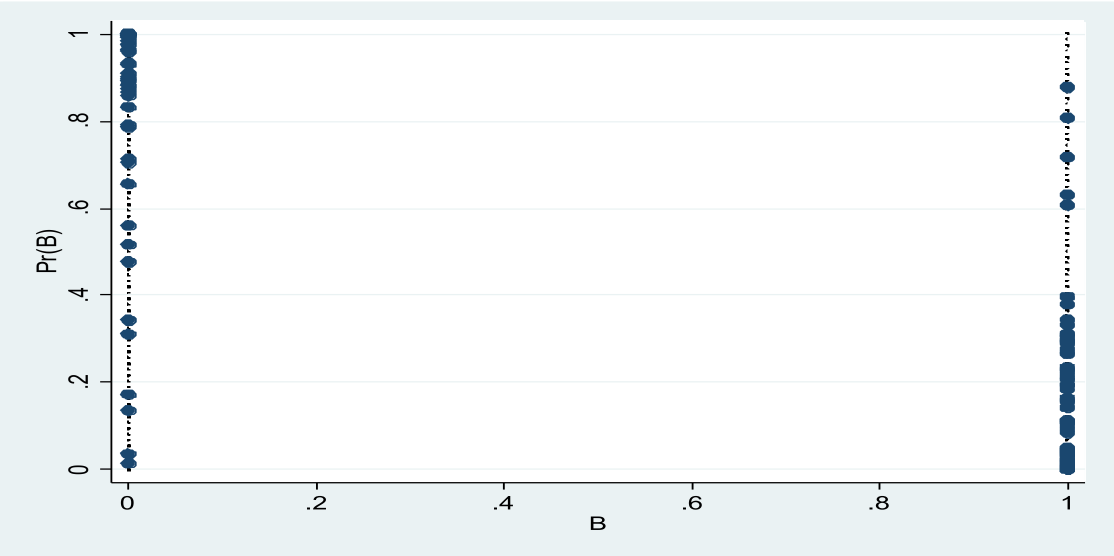
H_1: $b_1 \neq 0 \vee b_2 \neq 0 \vee b_3 \neq 0$

Table 4. 20: Wald Test for probit regression function on cluster CLB

```
. testparm f1 f2 f3 B

 ( 1)  [B]f1 = 0
 ( 2)  [B]f2 = 0
 ( 3)  [B]f3 = 0

           chi2(  3) =   41.96
         Prob > chi2 =    0.0000
```

According to table 4.20 above, P-value = 0 and is lower than significant level 0.05. We reject H_0 and accept H_1 which means there is at least one parameter in this model does not equal to 0 with a 5% statistical significance.

Graph 4. 6: Probability of default of observations predicted by the probit model



Probability of default for the observations are predicted according to the probit model, and the observations are divided into 2 groups according to cluster B which is transferred from cluster CLB. In cluster B, 0 represent default and 1 represent safe.

According to graph 4.6, there is a significant difference between the two groups in cluster CLB.

4.5 Comparison of Models

According to previous analysis, functions are created, and parameters of the function appeared. The information is indicated by table 4.21.

Table 4. 21: Information of functions

	2th ologit	3th logit	oprobit	probit
log likelihood	-87.508421	-37.344477	-88.891496	-37.836694
LR chi2(3)	162.27	137.33	159.51	136.35
Pseudo R^2	0.4811	0.6477	0.4729	0.6431

Information of the first and the third function is similar. Log likelihood of ordered logistic function is -87.51 comparing log likelihood of ordered probit function is -88.89. Pseudo R^2 of ordered logistic function is 0.4811 comparing pseudo R^2 of ordered probit function is 0.4729. Comparing Graph 4.3 and Graph 4.5, ability of first ordered logistic function to distinguish observations is better than the ordered probit function.

The second and the forth function provide similar information. Log likelihood of logit function is -37.34 comparing log likelihood of probit function is -37.84. Pseudo R^2 of logit function is 0.6477 comparing pseudo R^2 of probit function is 0.6433.

According to information in table 4.21, logit function and probit function are better than the ordered logistic function and ordered probit function.

In order to find how much observations are correctly classified by function; the model should be analyzed by STATA command *estat classification*. Take probit regression function as example, result is indicated in table 4.22.

Table 4. 22: Correctly classified rate probit regression function w

```
. estat clas,cutoff(0.432258)

Probit model for B

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |        83            12  |         95
     -     |         5            55  |         60
-----------+--------------------------+-----------
   Total   |        88            67  |        155

Classified + if predicted Pr(D) >= .432258
True D defined as B != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   94.32%
Specificity                     Pr( -|~D)   82.09%
Positive predictive value       Pr( D| +)   87.37%
Negative predictive value       Pr(~D| -)   91.67%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   17.91%
False - rate for true D         Pr( -| D)    5.68%
False + rate for classified +   Pr(~D| +)   12.63%
False - rate for classified -   Pr( D| -)    8.33%
--------------------------------------------------
Correctly classified                        89.03%
--------------------------------------------------
```

The overall rate of correct classification is estimated to be 89.03%, with 82.09% of the normal weight group correctly classified (specificity) and only 94.32% of the low weight group correctly classified (sensitivity). Classification is sensitive to the relative sizes of each component group, and always favors classification into the larger group. This phenomenon is evident here.

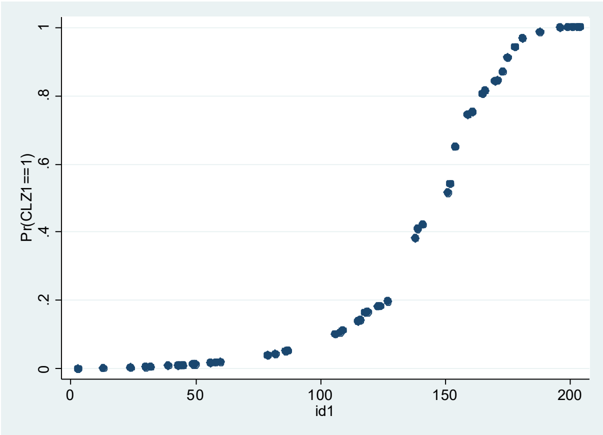
The logit regression function is also tested.

Comparing the correctly classified rate, logit function and probit function owns the same correctly classified rate which is 89.03%.

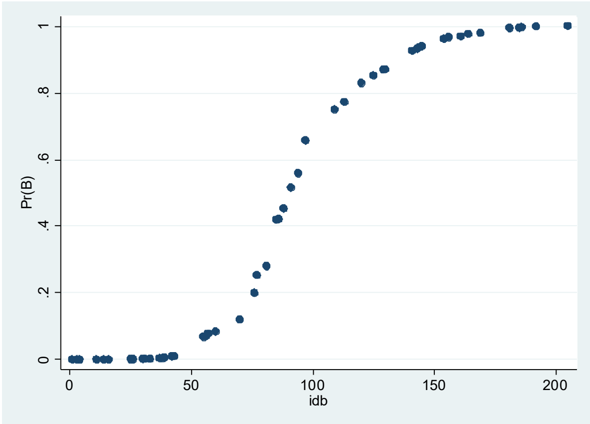
The two function can only be differed by other information except correctly classified rate. According to log likelihood, Pseudo R^2, the logistic regression model with cluster CLB where observations are divided into 2 groups based on standardized financial ratios is the best over the four.

Probability for the other 50 observations are predicted. Graph a is predicted by ordered logistic function; Graph b is predicted by logit function; Graph c is predicted by ordered probit function and graph d is predicted by probit function.

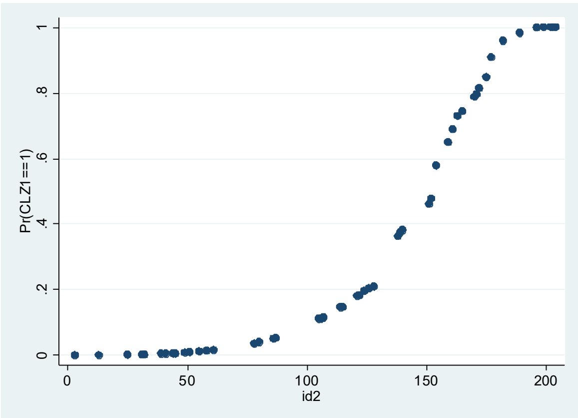
Graph 4. 7: Predicted probability of default for the first 50 observations



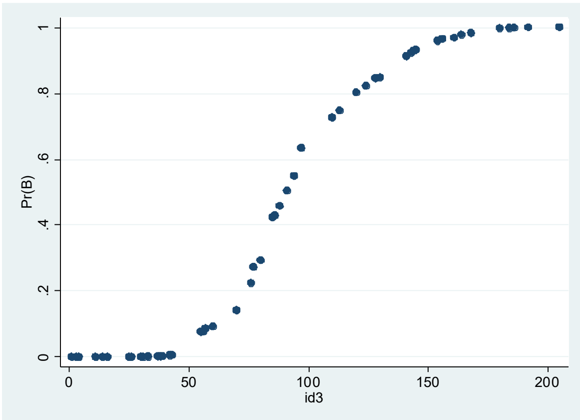
(a)



(b)



(c)



(d)

According to graph 4.4, ordered logistic regression model and ordered probit regression model has similar shape. Logistic regression model and probit regression model has similar shape. Based on previous analysis, graph b of logistic regression is best with highest correctly classification and significant.

Based on financial status of 155 observations and comparison of model, logistic regression model with correctly classification rate on 89.03% was finally defined as the best model for the observations.

5. Conclusion

SMEs in manufacturing industry are analyzed in quantitatively with financial ratios from statement of corporates. The finally defined model can be used by investors and banks to distinguish corporates with lower credit risk according to their financial statements. It can also help SMEs with good financial status finance easier by credit.

In this thesis, financial data of 205 observations are analyzed. Twelve of them are special treated. Altman Z-score was calculated and used to divided observations into groups.

In the fourth chapter, financial ratios are standardized and used in cluster analysis. Factor analysis finds the common part of variables and create common factor. The common factors explain more than 98% information provided by the origin variables. Creating suitable function to measure credit risk of observations, logistic and probit regression was applied. There are four functions computed finally. Coefficients of common factors are significant and not equals to zero.

In logit regression model and probit regression model, P-value of the constant terms are higher than 0.05 which means the constant term is not significant. But constant term may take information of unobserved effects, so it is kept.

Finally, the logistic function which is computed with observations divided into groups by standardized financial ratios was defined as the best credit measuring function for SMEs in manufacturing industry of China. This function can predict 89.03% default corporates correctly based on financial status of corporates.

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冯潇晓 Xiaoxiao Feng

Student's name and surname

Appendix—Origin Data (financial ratios of observations in 2017)

Stock Code	Current Ratio	Quick Ratio	Short-term debt /TL	L-T debt /TA	Gross Margin	Operating Margin	Net Margin %	Return on Assets %	Return on Equity %	Return on Invested Capital %
002001	3.83	3.12	0.7345	0.0613	50.47	36.54	27.34	11.52	15.48	13.12
002002	0.79	0.63	0.7778	0.1321	35.84	24.84	15.36	7.42	20.91	11.94
002003	2.79	2.00	0.9680	0.0059	42.64	19.78	13.89	12.77	15.82	15.8
002004	1.47	1.11	0.6321	0.2298	31.99	10.17	5.58	1.91	5.31	4.08
002005	0.96	0.80	0.6516	0.1942	14.84	-4.11	-23.11	-7.07	-16.85	-6.45
002006	1.59	1.13	0.3619	0.2714	28.89	13.71	10.43	5.83	10.15	8.32
002007	9.73	3.06	0.6981	0.0323	62.42	38.15	34.66	16.63	18.48	18.47
002008	1.44	1.04	0.8844	0.0584	41.27	19.16	14.4	13.61	27.1	20.89
002009	1.25	0.89	0.9445	0.0349	24.87	8.56	3.45	1.67	4.36	3.3
002011	0.94	0.67	0.8374	0.1111	17.02	4.35	1.11	0.72	2.09	2.34
002012	2.34	1.44	0.7631	0.0757	24.47	5.14	2.98	1.74	2.55	2.75
002013	1.42	1.00	0.7805	0.1351	26.17	11.53	6.27	2.74	7.22	5.43
002014	2.93	1.70	0.8662	0.0354	22.7	11.95	10.23	8.78	11.77	10.39
002015	10.29	4.97	0.6145	0.0443	8.31	2.83	1.82	2.32	2.55	2.46
002017	2.11	1.36	0.9006	0.0391	24.66	5.6	3.17	2.4	4.07	3.12
002019	2.30	1.50	0.7091	0.0770	57.23	37.9	29.84	16.57	26.12	21.06
002020	3.45	1.17	0.8945	0.0211	58.9	12.51	11.91	6.45	8.39	7.65
002021	1.41	0.73	0.9923	0.0036	17.9	-2.86	-9.3	-5.32	-9.48	-4.43
002022	3.28	2.02	0.7461	0.0672	41.31	16.76	13.66	8.64	11.33	10.53
002023	2.14	1.52	0.3865	0.2707	41.44	-2.07	8.07	0.56	0.96	1.32
002025	2.63	2.36	0.7620	0.1094	36.23	14.87	11.92	7.68	13.76	11.56
002026	3.25	2.06	0.9169	0.0171	25.49	11.32	8.54	4.39	5.47	5.06

002028	2.56	1.85	0.9399	0.0216	32.39	7.51	5.54	3.76	5.82	5.94
002029	1.96	0.62	0.9753	0.0090	40.66	17.53	10.26	3.84	5.95	4.09
002030	2.02	1.42	0.6775	0.2057	43.14	9.42	5.6	1.97	5.26	3.69
002031	1.85	0.69	0.5800	0.2397	36.35	22.4	5.52	1.08	2.14	2.66
002032	1.95	1.06	0.9969	0.0013	29.56	10.94	9.22	15.36	26.86	26.72
002035	1.63	0.85	0.9611	0.0188	45.47	10.36	8.89	13.06	25.98	22.48
002036	1.02	0.65	0.8717	0.0793	13.18	8.02	5.61	6.47	16.32	9.68
002037	1.35	1.27	0.8222	0.1310	20.14	7.83	1.67	1.01	3.76	4.57
002038	12.23	9.04	0.8377	0.0106	70.67	31.15	42.96	12.31	13.07	13.05
002042	1.16	0.43	0.9492	0.0290	11.19	7.97	5.38	5.01	12.46	7.39
002043	2.67	1.91	0.9449	0.0152	17.26	9.66	8.86	15.69	20.78	20.77
002045	1.22	0.84	0.6408	0.2349	15.67	5.25	3.23	3.65	9.4	5.61
002046	1.31	0.90	0.7855	0.0940	30.1	11.93	1.1	0.54	0.94	1.82
002048	1.42	1.03	0.8201	0.0930	21.11	9.97	5.39	5.37	12.29	9.06
002049	3.01	2.31	0.5361	0.1526	33.14	18.56	15.3	5.79	8.37	7.57
002050	2.34	1.39	0.8409	0.0578	31.23	16.73	12.9	11.91	18.73	14.64
002052	1.57	1.23	0.9894	0.0052	22.5	-3.7	1.33	0.48	0.97	1.93
002053	2.06	1.70	0.4664	0.1959	49.58	12.98	11.2	4.63	7.02	5.57
002054	1.83	1.31	0.6848	0.1287	22.03	4.89	1.22	1.01	1.67	2.15
002055	1.21	0.85	0.8168	0.1375	14.75	3.63	2.99	2.1	8.47	6.03
002056	2.16	1.13	0.9147	0.0261	23.15	10.85	9.62	9.34	13.56	11.81
002057	4.37	2.77	0.6328	0.0890	26.56	10.6	11.73	11.64	15.14	14.62
002058	5.83	3.30	0.9050	0.0152	38.22	1.2	2.52	1.28	1.5	1.38
002064	1.38	0.96	0.0354	0.3764	20.67	12.23	9.29	7.04	12.02	9.37
002066	1.00	0.61	0.9139	0.0765	22.83	5.65	0.7	0.43	3.78	4.2
002067	1.85	1.54	0.6455	0.1370	19.95	15.22	11.91	10.64	17.88	13.67

002068	1.07	0.79	0.8831	0.0672	18.48	10.58	6.92	7.05	18.45	10.11
002070	0.35	0.23	0.8881	0.1433	6.96	-18.55	-137.94	-44.51	-17.37	-62.54
002073	2.60	1.46	0.0573	0.4276	23.96	2.18	3.37	1.11	2.01	2.2
002074	1.80	1.48	0.7014	0.1550	39.14	25.63	17.32	6.14	13.78	10.1
002075	1.60	0.45	0.7519	0.1610	18.17	15.12	5.68	8.06	23.01	19.18
002076	1.34	0.76	0.9188	0.0423	28.18	10.39	5.45	2.87	5.39	4.65
002078	0.90	0.69	0.7555	0.1475	26.03	18.76	10.71	8.75	22.14	12.84
002079	3.93	3.09	0.7931	0.0465	18.99	11.18	5.65	5.6	6.99	6.49
002080	0.95	0.70	0.7112	0.1760	27.75	13.94	7.47	3.57	9.15	5.91
002082	2.65	1.65	0.7502	0.0810	1.55	0.56	0.67	5.23	7	6.31
002083	0.99	0.33	0.8479	0.0839	21.8	12.78	8.51	5.64	12.6	8.25
002084	2.56	1.75	0.7837	0.0730	21.33	6.69	4.44	4.27	6.55	6.09
002085	1.88	1.35	0.7119	0.1156	20.17	11.49	8.85	9.31	15.92	13.22
002087	1.91	0.68	0.4617	0.3461	17.28	10.46	5.62	3.43	9.42	6.53
002088	2.80	2.22	0.9728	0.0063	37.45	17.66	13.39	9.38	12.02	11.15
002089	0.76	0.46	0.7889	0.1314	12.61	3.48	-7.19	-2.31	-6.34	-0.06
002090	1.51	1.09	0.6984	0.2123	23.78	9.67	6.66	3.94	12.99	7.54
002092	0.77	0.49	0.6911	0.2070	17.85	9.46	5.85	4.7	13.86	7.84
002094	1.76	1.02	0.0381	0.4448	21.31	8.94	8.62	10.68	18.9	14.37
002096	1.20	0.95	0.8905	0.0530	25.71	4.48	1.03	0.65	1.33	1.64
002097	1.43	0.84	0.6814	0.2076	32.45	16.3	4.11	1.45	4.81	2.86
002098	1.20	0.52	0.6472	0.2177	34.57	11.19	6.4	5.13	10.13	7.06
002099	2.08	1.64	0.9428	0.0177	42.94	22.13	14.82	4.76	6.91	5.67
002100	2.03	1.16	0.6170	0.1886	23.4	10.06	8.79	7.86	14.5	9.27
002101	1.21	0.85	0.8724	0.0571	24.7	9.97	5.82	4.99	8.98	7.68
002102	1.33	0.65	0.7017	0.1058	6.58	4.69	2.9	3.69	5.73	5.13

002104	5.00	2.04	0.7514	0.0448	27.93	9.22	11.89	7.71	9.48	9.16
002105	1.08	0.74	0.8998	0.0638	15.73	5.34	2.62	3.22	9.06	6.23
002106	4.44	3.81	0.7345	0.0531	14.48	6.2	3.53	3.02	3.82	4.64
002107	2.84	2.53	0.7070	0.1052	78.44	16.76	7.85	7.31	11	11.48
002108	3.98	3.21	0.7998	0.0348	27.96	20.22	15.47	14.62	18.58	17.56
002109	0.82	0.72	0.0424	0.1853	18.38	14.98	10.9	4.82	6.39	5.63
002110	1.96	1.54	0.8826	0.0353	26.1	24.07	17.76	28.17	43.58	35.75
002111	1.67	0.80	0.9393	0.0254	35.78	13.98	6.28	2.62	4.31	3.96
002112	1.10	0.72	0.9313	0.0465	8.47	-16.85	-23.23	-10.38	-28.19	-11.45
002114	1.35	0.29	0.8126	0.0443	14.19	5.44	3.42	2.6	4.09	3.51
002115	0.95	0.59	0.8204	0.1035	26.55	4.89	4	1.36	3.41	3.29
002117	2.00	1.68	0.9099	0.0292	39.67	17.04	16.24	10.44	15.28	13.57
002118	1.92	0.49	0.7329	0.1429	79.69	50.42	28	4.79	9.44	7.44
002119	1.10	0.70	0.9257	0.0413	21.05	10.61	4.91	3.93	8.91	6.45
002121	1.04	0.77	0.6969	0.2096	29.89	11.62	10.48	3.32	12.39	7.56
002122	2.33	1.41	0.5034	0.2520	18.03	16.4	5.02	1.57	2.78	3.96
002124	1.22	0.41	0.5301	0.1502	24.43	9.01	8.56	7.56	11.82	9.78
002125	0.70	0.37	0.8023	0.1125	25.8	14.07	6.37	1.99	4.38	4.03
002126	1.32	0.80	0.8787	0.0600	26.16	10.98	7.19	5.42	11.02	9.02
002129	1.10	0.80	0.5536	0.2767	19.89	10.92	6.06	2.16	5.23	3.87
002130	0.87	0.61	0.6699	0.1847	29.27	10.09	6.51	2.9	6.26	5.7
002132	1.19	0.65	0.8409	0.0896	15.91	6.14	1.86	1.06	2.02	2.23
002134	1.69	0.98	0.9241	0.0235	11.94	-0.55	3.29	2.26	3.3	2.99
002136	1.28	0.76	0.9185	0.0264	22.78	16.27	14.33	16.72	27.98	22.71
002138	2.69	2.04	0.8631	0.0219	33.48	17.49	17.17	7.75	10.23	9.54
002139	1.69	1.20	0.9170	0.0330	23.97	11.35	7.83	7.09	11.51	10.05

002141	3.16	1.87	0.7230	0.0518	10.83	-0.11	0.79	0.6	0.7	0.56
002144	2.04	1.07	0.8184	0.0303	30.4	15.05	15.21	4.73	5.71	5.49
002145	0.98	0.68	0.8390	0.0763	32.95	19.67	11.93	7.11	13.98	9.18
002149	1.67	0.90	0.6528	0.1745	19.91	10.73	3.47	1.57	3.11	2.96
002150	3.86	2.42	0.8615	0.0320	25.68	10.87	5.81	5.03	6.53	6.23
002151	1.80	1.47	0.8230	0.0620	30.75	9.13	4.76	1.7	2.43	2.41
002152	2.90	1.49	0.8494	0.0453	41.82	15.58	20.52	7.31	10.42	10.03
002154	1.02	0.49	0.9387	0.0259	60.34	9.07	1	0.62	1.07	1.51
002156	1.19	0.89	0.6168	0.1963	14.46	5.27	1.87	1.05	2.48	2.9
002157	0.80	0.30	0.7104	0.1795	11.63	3.92	2.55	3.64	8.67	6.12
002158	2.34	1.21	0.7015	0.1289	34.83	15.7	14.14	8.18	12.2	8.71
002160	1.09	0.72	0.9709	0.0145	18.26	6.45	4.2	2.79	5.28	4.5
002161	1.63	0.94	0.9707	0.0074	41.94	-3.05	0.3	0.07	0.09	0.67
002162	0.69	0.33	0.8184	0.1066	34.61	6.43	2.24	0.97	2.35	3.04
002165	1.19	0.72	0.8237	0.0830	14.58	3.49	1.88	1.51	2.63	2.21
002166	1.20	0.08	0.9255	0.0475	26.67	26.69	25.7	7.73	21.72	16.69
002167	0.78	0.46	0.8108	0.1233	22.66	11.47	-4.62	-1.39	-3.72	3.46
002168	0.73	0.48	0.6943	0.1783	36.84	-20.04	-28.84	-4.08	-7.96	-6.14
002169	2.32	1.85	0.8226	0.0607	22.52	11.67	6.83	3.16	4.56	4.4
002170	0.78	0.23	0.8833	0.0687	14.15	-0.36	-4.88	-2.27	-5.07	-1.38
002171	2.77	1.18	0.9533	0.0129	5.89	4	3.27	7.95	10.9	8.44
002172	0.71	0.54	0.9589	0.0299	11	3.77	2.88	3.21	11.51	5.82
002176	1.09	0.80	0.8522	0.0830	25.98	12.56	8.36	3.32	7.25	5.07
002177	2.67	1.97	0.9078	0.0166	30.9	3.23	2.42	0.65	0.82	0.87
002179	1.83	1.49	0.8803	0.0613	35.04	17.12	12.97	8.9	18.35	12.8
002180	0.88	0.45	0.4084	0.5240	26.59	-11.3	4.45	2.15	32.52	8.99

002182	0.92	0.52	0.9321	0.0396	12.66	5.25	3.14	4.3	10.41	7.11
002184	1.82	1.49	0.9027	0.0471	20.3	4.38	0.71	0.67	1.31	1.94
002185	1.32	0.75	0.7243	0.1182	17.9	9.23	7.06	5.81	9.66	8.44
002189	2.16	1.85	0.7135	0.1139	16.17	4.74	2.38	2.44	3.99	3.66
002190	1.39	1.07	0.5868	0.3382	10.97	-9.29	-5.58	-1.2	-6.24	-2.15
002191	2.52	1.54	0.8578	0.0293	44.11	26.69	19.5	7.76	10.5	9.88
002192	1.63	1.01	0.6479	0.1006	41.76	13.16	12.96	3.63	4.81	4.8
002193	1.75	1.08	0.8360	0.0734	21.15	9.35	5.94	1.57	2.83	2.43
002194	2.79	2.02	0.9690	0.0082	-9.78	-29.45	-36.09	-22.5	-29.56	-26.98
002196	1.84	1.31	0.9380	0.0157	23.4	11.43	10.04	4.27	5.51	5.13
002197	1.58	1.04	0.7144	0.1369	26.02	8.2	2.56	0.86	1.57	1.51
002198	4.07	3.35	0.7192	0.0408	73.29	8.22	-45.88	-21.74	-24.76	-23.77
002199	1.74	1.24	0.9831	0.0036	12.35	-1.75	0.64	0.24	0.32	0.49
002201	0.78	0.54	0.6235	0.2555	22.7	5.38	-0.32	-0.12	-0.36	2.13
002202	1.12	0.87	0.5971	0.2774	30.24	13.37	12.16	4.45	14.32	8.07
002203	1.14	0.72	0.8321	0.1110	5.73	2.73	2.37	5.03	14.87	7.93
002204	1.39	0.95	0.9549	0.0256	23.01	-0.28	0.39	0.16	0.38	0.49
002205	0.82	0.66	0.8588	0.0891	21.22	5.65	2.02	0.68	1.72	1.66
002206	1.30	0.79	0.9691	0.0107	22.62	12.29	9.85	7.31	11.12	8.15
002209	1.17	0.71	0.9793	0.0128	26.12	4.45	2.1	1.22	3.24	3.2
002211	2.50	0.46	0.9471	0.0176	12.45	2.88	2.16	1.81	2.6	1.96
002212	4.13	2.15	0.5472	0.0755	24.76	9.9	8.28	4.58	6.27	6.11
002213	5.15	2.84	1.0000	0.0000	36.86	0.38	8.56	2.32	2.8	2.59
002214	3.20	1.74	0.8094	0.0573	53.48	19.82	10	2.25	3.06	3.13
002215	1.31	0.57	0.9187	0.0465	35.12	9.52	10.93	8.02	17.33	11.92
002216	1.10	0.55	0.9150	0.0460	33.92	2.07	1.37	1.69	3.69	3.27

002217	1.46	1.05	0.8204	0.0945	17.13	10.75	7.81	6.17	12.39	8.54
002218	0.95	0.60	0.7440	0.1299	25.12	17.55	10.77	3.09	5.89	5.05
002219	0.84	0.59	0.6850	0.1864	31.82	16.31	5.97	2.5	4.9	5.51
002220	6.44	3.46	0.1745	0.3817	22.11	17.6	9.13	2.7	4.95	4.34
002222	5.08	3.51	0.6590	0.0470	59.93	35.68	30.1	16.53	18.88	19.08
002223	4.98	3.88	0.6339	0.0755	39.66	18.53	16.72	9.52	11.67	11.29
002224	4.69	3.51	0.7350	0.0385	36.19	20.15	17.83	8.58	9.8	9.27
002225	1.76	1.14	0.8376	0.0824	29.7	8.17	0.79	0.47	0.94	1.8
002226	2.35	2.12	0.6545	0.1056	41.2	12.67	4.94	1.6	2.26	2.29
002227	2.96	1.89	0.8806	0.0296	40.88	7.94	4.05	1.43	1.85	1.72
002228	1.40	0.96	0.8192	0.1091	14.34	5.85	1.62	2.38	6.29	6.99
002229	3.62	2.84	0.7264	0.0615	24.06	3.34	1.55	0.47	0.65	0.74
002231	3.09	2.16	0.9670	0.0102	17.28	4.84	1.9	1.02	1.4	1.32
002233	3.23	1.06	0.9432	0.0095	29.52	20.4	15.8	8.73	11.21	10.86
002236	1.77	1.40	0.9172	0.0422	38.23	16.31	12.62	12.96	25.44	17.55
002237	0.98	0.18	0.9809	0.0129	7.24	4.35	1.85	2.75	9	6.39
002239	1.48	1.06	0.8529	0.0590	21.48	7.9	7.08	4.32	7.28	5.82
002240	1.58	0.58	0.9042	0.0297	7.87	3.03	1.3	0.96	1.52	2.73
002241	1.27	0.95	0.8994	0.0441	22.01	11.83	8.38	8.65	16.62	11.84
002242	2.04	1.45	0.9897	0.0034	33.01	10.08	9.51	12.59	19.63	18.94
002243	2.76	1.91	0.7515	0.0544	21.87	6.51	3.45	2.27	2.85	2.93
002246	2.35	1.77	0.7770	0.0791	23.63	5.95	4.97	4.23	6.24	5.73
002248	0.71	0.27	0.9504	0.0278	-14.7	-2	33.48	2.17	5.62	8.24
002249	1.48	1.06	0.7607	0.1113	20.28	7.23	4.85	2.65	4.72	3.89
002250	2.39	1.54	0.4560	0.1907	31.29	7.43	4.9	2.75	4.04	3.86
002252	10.45	8.67	0.3335	0.0919	63.69	43.45	43.36	6.04	6.92	7.03

002254	4.28	3.21	0.6793	0.0721	16.32	7.53	6.44	3.84	4.97	4.72
002255	1.39	0.81	0.9235	0.0403	24.16	11.21	8.29	1.87	3.54	3.13
002256	0.91	0.82	0.8715	0.0525	35.79	26.5	23.48	4.26	6.83	5.62
002258	1.41	0.85	0.6658	0.1583	28.74	18.07	13.04	10.54	18.22	14.32
002260	0.47	0.28	0.9792	0.0262	23.11	-5.84	-67.5	-62.8	-591.2	-100.32
002262	3.04	2.03	0.8694	0.0339	47.97	13.61	11.63	12.58	17.35	14.87
002263	1.27	0.87	0.8314	0.0584	6.69	-2.74	-54.13	-15.58	-23.13	-15.74
002265	1.90	1.16	0.8388	0.0544	18.35	3.14	2.18	1.74	2.69	2.76
002266	0.97	0.48	0.6990	0.1816	20.52	0.24	7.9	1.2	2.87	2.69
002269	1.08	0.31	1.0000	0.0000	47.45	2.75	-4.71	-4.76	-10.2	-5.5
002270	2.70	2.23	0.9709	0.0092	36.29	22.75	16.94	11.25	15.14	13.5
002271	1.91	1.48	0.7526	0.1224	37.73	16.2	12.04	11.17	21.2	14.87
002272	2.97	2.35	0.8682	0.0334	19.9	1.33	1.06	0.4	0.55	0.53
002273	4.36	3.01	0.3660	0.2056	30.67	16.98	16.59	8.32	11.17	8.5
002274	0.43	0.20	0.8994	0.0582	10.31	3.38	1.08	0.92	2.12	2.26
002275	4.21	2.95	0.7963	0.0367	75.91	33.36	28.74	15.23	18.29	17.25
002276	2.20	1.70	0.8298	0.0740	13.75	2.33	1.55	1.9	3.26	3.38
002278	2.74	1.63	0.7976	0.0647	36.59	5.13	2.05	0.66	0.99	0.91
002281	2.23	1.49	0.8786	0.0487	20.83	9	7.34	6.7	11.28	8.72
002282	1.67	1.07	0.9412	0.0149	32.74	7.1	8.63	3.02	3.99	3.75
002283	1.29	0.89	0.9248	0.0282	26.77	15.1	11.09	5.89	8.99	7.15
002284	1.54	0.85	0.7141	0.1554	14.93	4.36	2.1	1.49	3.03	2.19
002427	0.92	0.81	0.7687	0.1784	24.62	15.05	6.41	4.81	16.34	8.44
002450	2.14	1.99	0.7235	0.1310	39.92	29.04	20.99	8.15	14.73	10.69
002570	0.97	0.64	0.7915	0.1319	60.12	-10.61	-39.73	-19.11	-44.56	-23.92
002604	0.49	0.35	0.7361	0.2870	13.6	-0.88	-177.19	-84.15	-258	-91.86

002680	6.12	2.02	0.8596	0.0204	86.55	39.19	36.45	13.25	15.26	15.02	
Stock Code	FFC/Net Income	Days Inventory	Receivables Turnover	Inventory Turnover	Fixed-assets Turnover	Asset Turnover	Payables Period	EM	Debt to equity	Debt to Assets	**Z**
002001	0.15	165.2	4.85	2.21	1.23	0.42	93.45	1.30	0.30	0.2308	2.1297
002002	0.69	51.97	5.11	7.02	0.81	0.48	73.09	2.47	1.47	0.5946	1.0655
002003	0.4	69.89	7.34	5.22	2.42	0.92	62.25	1.23	0.23	0.1842	2.8493
002004	-0.75	101.2	3.68	3.61	2.18	0.34	48.32	2.66	1.66	0.6246	0.8093
002005	0.17	82.73	3.65	4.41	0.97	0.3	80.65	2.26	1.26	0.5575	0.2232
002006	-1.13	159	4.83	2.3	3.18	0.56	115.3	1.74	0.74	0.4253	1.5365
002007	0.08	437.1	4.44	0.83	2.06	0.48	26.91	1.12	0.12	0.1071	3.5893
002008	0.59	111.2	3.8	3.28	6.13	0.94	78.27	2.02	1.02	0.5050	2.0097
002009	-0.99	152.3	2.19	2.4	2.69	0.48	121.5	2.69	1.69	0.6283	0.9771
002011	-2.84	73.29	4.99	4.98	4.63	0.65	88.49	3.16	2.16	0.6835	0.8231
002012	1.7	119.6	4.57	3.05	1.69	0.58	45.69	1.47	0.47	0.3197	1.8657
002013	1.87	180.1	2.07	2.03	1.66	0.44	214.7	2.60	1.60	0.6154	1.1265
002014	0.98	69.56	5.11	5.24	2.78	0.86	44.55	1.36	0.36	0.2647	2.5486
002015	1.05	108	16.18	3.38	6.43	1.27	11.12	1.13	0.13	0.1150	3.5750
002017	1.74	155.1	8.06	2.35	5.4	0.76	110.8	1.65	0.65	0.3939	2.0478
002019	0.5	75.01	5.66	4.87	5.12	0.56	44.54	1.36	0.36	0.2647	2.0966
002020	1.03	110.1	6.59	3.32	3.09	0.54	71.76	1.25	0.25	0.2000	1.8346
002021	-0.07	97.84	4.93	3.73	4.35	0.57	87.56	1.88	0.88	0.4681	0.9675
002022	0.12	138.1	5.64	2.64	4.82	0.63	48.62	1.36	0.36	0.2647	1.8086
002023	-18.11	482.1	0.77	0.76	0.16	0.07	240.4	1.79	0.79	0.4413	0.5991
002025	0.18	68.14	2.49	5.36	4.77	0.64	157.9	1.85	0.85	0.4595	1.9811
002026	0.45	155.2	3.7	2.35	2.08	0.51	74.92	1.26	0.26	0.2063	1.8744
002028	1.74	97.67	1.95	3.74	8.1	0.68	132.3	1.56	0.56	0.3590	2.2891

002029	1.62	175.6	13.38	2.08	7.99	0.37	89.54	1.57	0.57	0.3631	1.4258
002030	-4.76	87.61	1.73	4.17	3.14	0.35	80.33	2.76	1.76	0.6377	1.0978
002031	0.87	270.7	2.23	1.35	0.92	0.2	78.05	2.33	1.33	0.5708	1.0567
002032	0.71	70.9	11.11	5.15	16.27	1.67	79.78	1.76	0.76	0.4318	3.3286
002035	0.58	48.47	17.42	7.53	10.03	1.47	70.36	1.93	0.93	0.4819	2.8383
002036	-1.5	57.84	5.44	6.31	3.03	1.15	52.43	2.62	1.62	0.6183	1.6231
002037	7.8	25.25	1.52	14.46	3.77	0.61	161.9	3.80	2.80	0.7368	1.1675
002038	0.28	237.4	2.01	1.54	2.39	0.29	71.34	1.07	0.07	0.0654	3.7284
002042	-3.75	121.8	15.29	3	2.75	0.93	30.79	2.33	1.33	0.5708	1.4189
002043	0.96	30.4	61.27	12.01	16.05	1.77	21.38	1.38	0.38	0.2754	3.5371
002045	-3.33	48.83	3.75	7.47	5.64	1.13	78.45	2.89	1.89	0.6540	1.4840
002046	-2.16	136.1	5.64	2.68	1.39	0.49	85.26	1.78	0.78	0.4382	1.0162
002048	0.33	59.57	5.58	6.13	4.67	1	86.54	2.07	1.07	0.5169	1.7682
002049	1	169.2	2.5	2.16	6.11	0.38	59.88	1.49	0.49	0.3289	1.7586
002050	0.04	84.78	6.86	4.31	3.6	0.92	66.27	1.57	0.57	0.3631	2.3839
002052	-17.73	112.6	1.72	3.24	2.52	0.36	102.4	1.96	0.96	0.4898	0.6590
002053	-3.27	67.88	9.04	5.38	0.9	0.41	121.9	1.58	0.58	0.3671	1.3093
002054	0.21	45.89	5.84	7.95	3.46	0.82	20.68	1.69	0.69	0.4083	1.9009
002055	-4.04	106.2	3.77	3.44	5.46	0.7	125.6	4.01	3.01	0.7506	1.0148
002056	0.59	47	7.37	7.77	2.82	0.97	65.05	1.44	0.44	0.3056	2.6073
002057	0.35	44.13	5.41	8.27	4.07	0.99	31.55	1.32	0.32	0.2424	2.4788
002058	1.23	197.8	4.09	1.85	4.92	0.51	87.31	1.19	0.19	0.1597	4.0133
002064	0.69	64.6	9.64	5.65	1.72	0.76	48.95	1.64	0.64	0.3902	2.0143
002066	7.17	169.4	2.7	2.15	2.6	0.62	111.7	8.97	7.97	0.8885	0.7742
002067	-0.07	31.52	11.01	11.58	1.87	0.89	21.09	1.63	0.63	0.3865	2.0763
002068	0.03	47.01	6.27	7.76	2.22	1.02	39.66	2.35	1.35	0.5745	1.5535

002070	-0.04	219.6	1.71	1.66	1.35	0.32	85.2	37.91	36.91	0.9736	(2.5552)
002073	0.91	248.1	1.94	1.47	1.63	0.33	113	1.83	0.83	0.4536	1.2417
002074	-1.74	132.9	1.62	2.75	1.52	0.35	263.6	2.08	1.08	0.5192	1.1305
002075	2.33	62.08	243.96	5.88	3.65	1.42	45.42	2.85	1.85	0.6491	1.9775
002076	-8.91	187.4	2.62	1.95	3.56	0.53	91.64	2.09	1.09	0.5215	1.2892
002078	-0.11	34.78	12.57	10.49	1.46	0.81	45.86	2.52	1.52	0.6032	1.5008
002079	0.84	46.17	6.6	7.91	3.69	0.99	37.26	1.29	0.29	0.2248	3.0903
002080	-1.01	81.76	4.15	4.46	0.92	0.48	102.2	2.56	1.56	0.6094	0.8121
002082	-0.39	7.73	119.09	47.22	32.04	7.79	2.48	1.48	0.48	0.3243	8.1770
002083	0.54	188.5	11.04	1.94	1.72	0.66	46.57	2.23	1.23	0.5516	1.2512
002084	0.78	82.31	5.11	4.43	4.11	0.96	48.98	1.51	0.51	0.3377	2.1215
002085	0.33	48.05	5.58	7.6	2.89	1.05	41.14	1.67	0.67	0.4012	2.5031
002087	-2.53	145.8	8.96	2.5	1.92	0.61	16.97	2.80	1.80	0.6429	1.3563
002088	1.6	74.34	3.99	4.91	2.36	0.7	58.56	1.30	0.30	0.2308	2.4013
002089	0.42	52.16	2.75	7	1.45	0.32	34.38	2.65	1.65	0.6226	0.5997
002090	-1.03	103.6	2.14	3.52	3.26	0.59	130	3.38	2.38	0.7041	1.3113
002092	0.06	24.05	37.38	15.18	1.45	0.8	48.35	3.03	2.03	0.6700	1.0042
002094	-0.12	53.79	9.74	6.79	22.46	1.24	20.4	1.86	0.86	0.4624	2.1668
002096	-9.45	41.32	5.25	8.83	2.45	0.63	35.84	1.94	0.94	0.4845	1.3158
002097	-3.58	243.2	1.49	1.5	1.13	0.35	110.5	2.87	1.87	0.6516	0.8307
002098	-0.38	141.8	5.97	2.57	3.01	0.8	60.93	2.61	1.61	0.6169	1.1849
002099	-0.14	199.6	5.06	1.83	1.66	0.32	68.04	1.45	0.45	0.3103	1.4742
002100	0.16	92.33	26.08	3.95	2.6	0.89	15.99	1.97	0.97	0.4924	1.9138
002101	0.75	57.2	4.24	6.38	2.81	0.86	89.63	1.81	0.81	0.4475	0.9755
002102	-0.17	20.23	24.51	18.04	9.31	1.27	10.31	1.55	0.55	0.3548	2.1277
002104	-2.7	81.74	6.74	4.47	4.24	0.65	53.27	1.22	0.22	0.1803	3.1326

002105	-0.59	56.89	4.72	6.42	3.68	1.23	66.66	2.75	1.75	0.6364	1.7202
002106	2.02	42	3.6	8.69	2.79	0.86	53.85	1.25	0.25	0.2000	2.2678
002107	1.91	137.3	7.91	2.66	3.2	0.93	48.02	1.56	0.56	0.3590	2.7211
002108	0.3	41.86	4.75	8.72	2.66	0.94	29.77	1.21	0.21	0.1736	3.7929
002109	2.34	17.72	20.33	20.59	0.58	0.44	26.15	1.24	0.24	0.1935	1.3950
002110	0.55	33.31	6661.48	10.95	3.41	1.59	21.61	1.43	0.43	0.3007	2.6165
002111	-0.44	313	2.26	1.17	2.09	0.42	91.51	1.72	0.72	0.4186	1.1905
002112	-0.32	171.3	1.37	2.13	2.62	0.45	102.2	3.09	2.09	0.6764	0.4545
002114	-2.33	94	121.75	3.88	2.5	0.76	31.99	1.31	0.31	0.2366	1.0796
002115	-4.46	172.3	2.5	2.11	1.82	0.34	265.8	2.36	1.36	0.5763	0.5020
002117	0.72	55.24	4.47	6.61	1.92	0.64	79.26	1.48	0.48	0.3243	2.1264
002118	-4.23	5082	1.95	0.07	0.8	0.17	252.2	2.15	1.15	0.5349	1.1694
002119	-0.46	92.76	4.1	3.94	2.12	0.8	37.08	2.25	1.25	0.5556	1.4597
002121	-2.38	146.1	1.47	2.5	1.03	0.32	257.9	3.24	2.24	0.6914	0.6719
002122	-6.79	227.3	2.86	1.61	1.55	0.31	84.74	2.03	1.03	0.5074	1.2367
002124	-2.49	117.2	34.92	3.11	2.43	0.88	37.68	1.47	0.47	0.3197	1.7469
002125	-4.51	178.1	3.79	2.05	0.54	0.31	128.6	2.32	1.32	0.5690	0.4002
002126	-0.23	75.77	3.51	4.82	2.62	0.75	137.6	1.98	0.98	0.4949	1.4358
002129	-4.85	72.83	8.29	5.01	0.73	0.36	81.11	2.63	1.63	0.6198	0.6191
002130	-1.28	79.56	3.33	4.59	1.39	0.45	79.7	2.27	1.27	0.5595	0.9963
002132	-4.37	59.65	4.53	6.12	1.62	0.57	43.61	2.29	1.29	0.5633	0.8727
002134	1.03	82.92	4.04	4.4	1.35	0.69	97.19	1.45	0.45	0.3103	1.4615
002136	1.26	51.11	27.04	7.14	1.93	1.17	55.32	1.48	0.48	0.3243	2.3815
002138	0.33	89.52	2.82	4.08	0.83	0.45	48.74	1.19	0.19	0.1597	1.9202
002139	-0.5	54.7	4.39	6.67	3.85	0.91	82.96	1.66	0.66	0.3976	2.0808
002141	-5.25	39.24	5.38	9.3	6.01	0.76	30.37	1.23	0.23	0.1870	3.3605

002144	1.16	42.79	4.16	8.53	2.1	0.31	122.4	1.20	0.20	0.1667	1.3526
002145	0.34	68.4	10.44	5.34	1.33	0.6	65.65	1.90	0.90	0.4737	1.3194
002149	-6.11	204.5	3.71	1.78	1.17	0.45	72.29	2.01	1.01	0.5025	0.8388
002150	0.48	45.98	6.55	7.94	4.27	0.86	64.92	1.30	0.30	0.2308	2.6149
002151	-2.68	114.4	2.42	3.19	3.72	0.36	107.5	1.54	0.54	0.3506	0.8697
002152	0.55	276.3	5.63	1.32	4.61	0.36	67.7	1.43	0.43	0.3007	1.9757
002154	10.88	284.9	6.52	1.28	3.47	0.61	85.44	1.73	0.73	0.4220	1.4171
002156	-5.3	57.5	4.68	6.35	1.1	0.56	107.3	2.05	1.05	0.5122	0.8955
002157	-6.12	54.14	48.73	6.74	2.8	1.43	28.33	2.63	1.63	0.6198	1.6002
002158	0.37	87.57	7.4	4.17	2.57	0.58	93.45	1.76	0.76	0.4318	1.8371
002160	-2.05	96.24	4.8	3.79	2.48	0.66	56.73	1.99	0.99	0.4975	0.8809
002161	-37.96	367.1	2.29	0.99	3.03	0.23	104.8	1.34	0.34	0.2537	1.3616
002162	3.25	209.8	7.13	1.74	1.45	0.43	120.2	2.42	1.42	0.5868	0.6307
002165	-14.59	61.32	7.35	5.95	1.95	0.8	46.8	1.89	0.89	0.4709	1.4269
002166	0.44	993	12.23	0.37	1.51	0.3	225.3	2.76	1.76	0.6377	1.0148
002167	-3.9	115.9	2.35	3.15	0.8	0.3	44.69	2.87	1.87	0.6516	0.3741
002168	0.1	99.49	2.56	3.67	3.6	0.14	160.5	2.40	1.40	0.5833	0.2672
002169	-1.9	79.98	1.43	4.56	1.51	0.46	93	1.52	0.52	0.3421	1.4938
002170	-1.77	67.63	24.21	5.4	1.39	0.47	37.83	2.43	1.43	0.5885	0.6064
002171	-0.13	28.63	22.13	12.75	17.24	2.44	6.98	1.38	0.38	0.2754	3.6517
002172	-4.02	35.91	18.3	10.16	2.37	1.11	48.32	3.67	2.67	0.7275	0.9801
002176	-3.82	110.8	3.43	3.29	2.17	0.4	174.5	2.28	1.28	0.5614	0.8723
002177	6.88	192.9	3.39	1.89	1.33	0.27	57.57	1.22	0.22	0.1803	2.4449
002179	0.23	115.5	2.51	3.16	3.97	0.69	131.1	2.05	1.05	0.5122	1.8329
002180	-0.29	67.66	8.53	5.39	5.47	0.48	80.01	8.75	7.75	0.8857	0.4510
002182	0.35	53.06	6.72	6.88	3.43	1.36	25.41	2.40	1.40	0.5833	1.5940

002184	-10.68	62.31	2.42	5.85	6.9	0.95	82.62	1.94	0.94	0.4845	1.7562
002185	-1.81	72.37	8.56	5.04	1.58	0.82	86.07	1.75	0.75	0.4286	1.6907
002189	3.25	31.44	3.67	11.61	2.64	1.02	81.93	1.66	0.66	0.3976	2.0670
002190	8.56	160.2	2.25	2.28	0.56	0.22	121.1	5.51	4.51	0.8185	0.3423
002191	0.79	149.3	3.97	2.44	1.46	0.4	145.3	1.26	0.26	0.2063	2.0240
002192	-0.29	160.3	2.57	2.28	1.7	0.28	82.69	1.40	0.40	0.2857	1.0308
002193	-0.83	193.5	2.71	1.89	1.08	0.26	97.13	1.81	0.81	0.4475	0.9601
002194	0.75	108.5	4.94	3.36	3.04	0.62	63.85	1.36	0.36	0.2647	1.0426
002196	-0.71	125.3	2.7	2.91	2.63	0.43	110.8	1.34	0.34	0.2537	1.2803
002197	-29.64	90.45	1.73	4.04	1.3	0.33	169.6	1.92	0.92	0.4792	0.8453
002198	-0.06	162.8	3.11	2.24	1.78	0.47	33.65	1.17	0.17	0.1453	2.6986
002199	-11.33	91.8	4.07	3.98	0.76	0.37	152	1.27	0.27	0.2126	1.0326
002201	-9.84	116.1	3.6	3.15	0.69	0.39	101.7	3.11	2.11	0.6785	0.5078
002202	-0.62	75.74	1.7	4.82	1.19	0.37	210.1	3.21	2.21	0.6885	0.7884
002203	-4.99	28.32	10.54	12.89	20.04	2.13	32.38	2.95	1.95	0.6610	2.4262
002204	2.68	238	1.23	1.53	2.14	0.41	331	2.31	1.31	0.5671	1.0182
002205	1.03	90.82	1.44	4.02	1.65	0.34	263.2	2.71	1.71	0.6310	0.4688
002206	-0.01	67.97	6.87	5.37	1.51	0.74	21.74	1.53	0.53	0.3464	1.7932
002209	4.84	207.6	2.27	1.76	2.4	0.58	148.7	2.61	1.61	0.6169	1.0350
002211	5.23	36.06	11.57	10.12	4.81	0.84	15.05	1.50	0.50	0.3333	1.2354
002212	-0.01	62.2	4.4	5.87	7.58	0.55	16.1	1.20	0.20	0.1667	1.6564
002213	-0.7	170.7	3.13	2.14	1.37	0.27	142.5	1.18	0.18	0.1537	3.4272
002214	-0.9	1064	0.79	0.34	1.19	0.23	188.3	1.43	0.43	0.3007	1.8769
002215	-1.69	140.6	7.73	2.6	9.56	0.73	47.61	2.34	1.34	0.5726	1.4697
002216	1.89	106.1	13.05	3.44	3.27	1.23	118.5	2.18	1.18	0.5413	1.8303
002217	-1.46	80.85	4.13	4.51	4.15	0.79	75.57	2.11	1.11	0.5261	1.5029

002218	-1.3	154.3	2.31	2.37	0.52	0.29	88.5	2.03	1.03	0.5074	0.6985
002219	-3.84	108.2	2.35	3.37	1.59	0.42	65.22	2.45	1.45	0.5918	0.7572
002220	-2.4	77.21	1.35	4.73	0.64	0.3	10.51	1.86	0.86	0.4624	1.4316
002222	0.38	234.5	5.77	1.56	1.3	0.55	56.78	1.16	0.16	0.1379	4.0208
002223	-0.42	86.5	5.42	4.22	5.08	0.57	66.3	1.26	0.26	0.2063	2.3112
002224	0.33	120.3	16.84	3.03	1.94	0.48	57.21	1.17	0.17	0.1453	3.2170
002225	5.27	182.4	1.6	2	4.32	0.59	158.6	2.03	1.03	0.5074	1.3699
002226	2.54	42.03	3.84	8.69	1.68	0.32	40.71	1.44	0.44	0.3056	1.3294
002227	-2.3	393.3	1.36	0.93	1.82	0.35	129.3	1.33	0.33	0.2481	1.7015
002228	-2.92	54.04	4.73	6.75	6.28	1.47	49.05	2.52	1.52	0.6032	2.1858
002229	0.93	120	6.55	3.04	1.09	0.31	88.79	1.29	0.29	0.2248	1.6497
002231	-10.36	193.8	1.25	1.88	10.67	0.54	118.6	1.45	0.45	0.3103	2.1786
002233	0.5	48.16	39.43	7.58	1.56	0.55	83.4	1.20	0.20	0.1667	2.0640
002236	0.26	78.57	2.74	4.65	16.48	1.03	72.82	2.04	1.04	0.5098	2.2921
002237	0.84	100.4	1507.33	3.64	5.04	1.49	31.3	3.07	2.07	0.6743	1.7724
002239	0.58	87.53	3.82	4.17	3.8	0.61	98.43	1.67	0.67	0.4012	1.6834
002240	-6.03	104.9	19.68	3.48	1.49	0.74	27.13	1.45	0.45	0.3103	1.2400
002241	-0.01	49.73	4.37	7.34	2.66	1.03	75.22	1.78	0.78	0.4382	2.0066
002242	0.02	34.76	67.8	10.5	11.13	1.32	82.16	1.50	0.50	0.3333	2.9427
002243	-0.71	64.14	3.5	5.69	1.34	0.66	55.21	1.28	0.28	0.2188	1.8588
002246	-0.24	80.45	6.12	4.54	2.8	0.85	73.17	1.55	0.55	0.3548	1.7176
002248	3.14	1186	1.37	0.31	0.12	0.06	340.7	2.27	1.27	0.5595	(0.2018)
002249	-1.23	83.52	4.13	4.37	3.41	0.55	115.9	1.87	0.87	0.4652	1.0859
002250	0.41	119.5	5.47	3.06	1.13	0.56	54.52	1.54	0.54	0.3506	1.4519
002252	0.13	510.4	2.92	0.72	1.66	0.14	24.89	1.16	0.16	0.1379	2.7904
002254	2.99	68.55	12.73	5.32	1.62	0.59	76.52	1.29	0.29	0.2248	2.4045

002255	1.62	341.7	0.98	1.07	1.7	0.23	277.3	2.11	1.11	0.5261	0.7715
002256	-1.88	40.15	2.33	9.09	0.41	0.18	216.1	1.69	0.69	0.4083	1.1361
002258	-0.53	81.22	5.92	4.49	1.55	0.81	56.91	1.90	0.90	0.4737	1.6310
002260	0.29	89.11	8.9	4.1	7.71	0.93	73.35	23.64	29.76	1.2588	(2.9108)
002262	0.73	68.06	4.97	5.36	4.44	1.08	49.28	1.35	0.35	0.2593	3.2812
002263	-0.03	66.94	6.85	5.45	0.51	0.29	45.04	1.53	0.53	0.3464	0.6281
002265	0.56	121.8	5.27	3	2.5	0.8	76.39	1.51	0.51	0.3377	1.4203
002266	-3.29	391.8	3.53	0.93	0.73	0.15	244.4	2.52	1.52	0.6032	0.6047
002269	1.91	236.2	16.42	1.55	4.48	1.01	115.6	2.33	1.33	0.5711	1.2423
002270	-0.95	123.5	2.45	2.96	4.96	0.66	58.32	1.46	0.46	0.3151	2.5477
002271	-0.87	63.24	2.87	5.77	4.48	0.93	41.25	1.98	0.98	0.4949	2.0904
002272	-0.12	123.7	1.38	2.95	1.33	0.38	122.8	1.34	0.34	0.2537	1.6661
002273	-0.8	53.54	4.4	6.82	1.52	0.5	71.97	1.48	0.48	0.3243	1.7509
002274	-2.96	36.86	32.2	9.9	1.34	0.86	36.42	2.37	1.37	0.5781	0.7410
002275	0.7	165.1	15.34	2.21	1.57	0.53	113	1.22	0.22	0.1803	2.6991
002276	-10.34	38.53	3.21	9.47	9.24	1.23	28.24	1.77	0.77	0.4350	2.0832
002278	1.11	338.2	1.1	1.08	1.8	0.32	302.6	1.47	0.47	0.3197	1.4740
002281	-0.14	129.4	4.87	2.82	5.67	0.91	95.61	1.67	0.67	0.4012	2.1560
002282	-0.18	194.6	2.24	1.88	1.79	0.35	89.52	1.34	0.34	0.2537	1.0668
002283	-0.91	110.9	3.69	3.29	0.99	0.53	67.53	1.60	0.60	0.3750	1.4067
002284	-2.85	78.52	5.25	4.65	2.12	0.71	119	2.19	1.19	0.5434	1.2302
002427	-1.54	34.1	4.78	10.7	2.7	0.75	56.09	4.37	3.37	0.7712	1.0692
002450	1.34	30.51	2.56	11.97	3.24	0.39	40.44	1.90	0.90	0.4737	1.5670
002570	0.25	230	2.7	1.59	1.55	0.48	147	2.72	1.72	0.6324	(0.1008)
002604	0.11	31.93	12.38	11.43	1.26	0.47	35.78	3.07	2.07	1.0875	(3.5678)
002680	0.29	420.8	2.13	0.87	3	0.36	114.8	1.17	0.17	0.1453	3.0610